HAXAD:
Anomaly Detection in the Higgs Peak

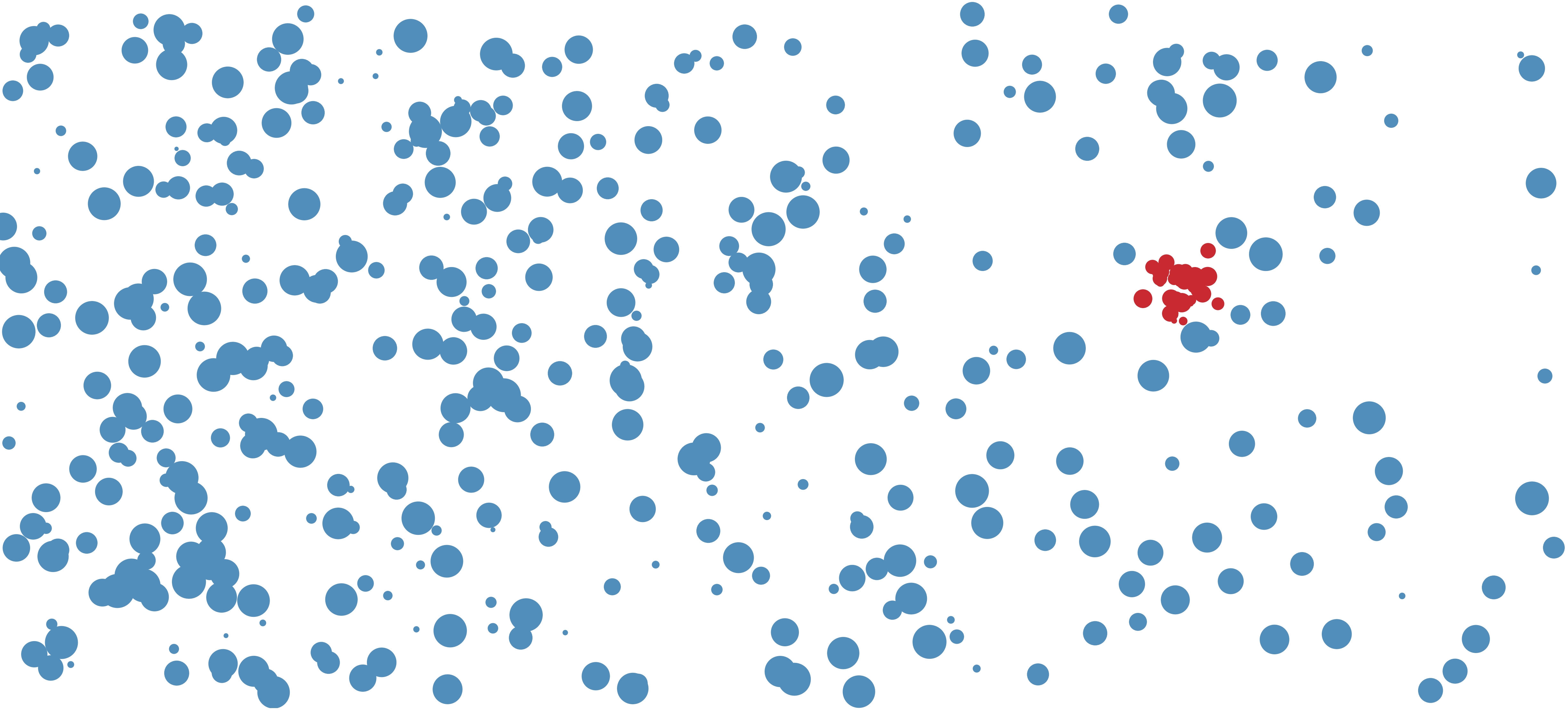
[2508.13566, 2607.19323]

Chi Lung Cheng, Julia Gonski, Runze Li, Qibin Liu, Benjamin Nachman,
Dennis Noll, Julie Khalilieh Romman, Liangyu Wu

ML4Jets

Sept 17th, 2026

Finding an Anomaly



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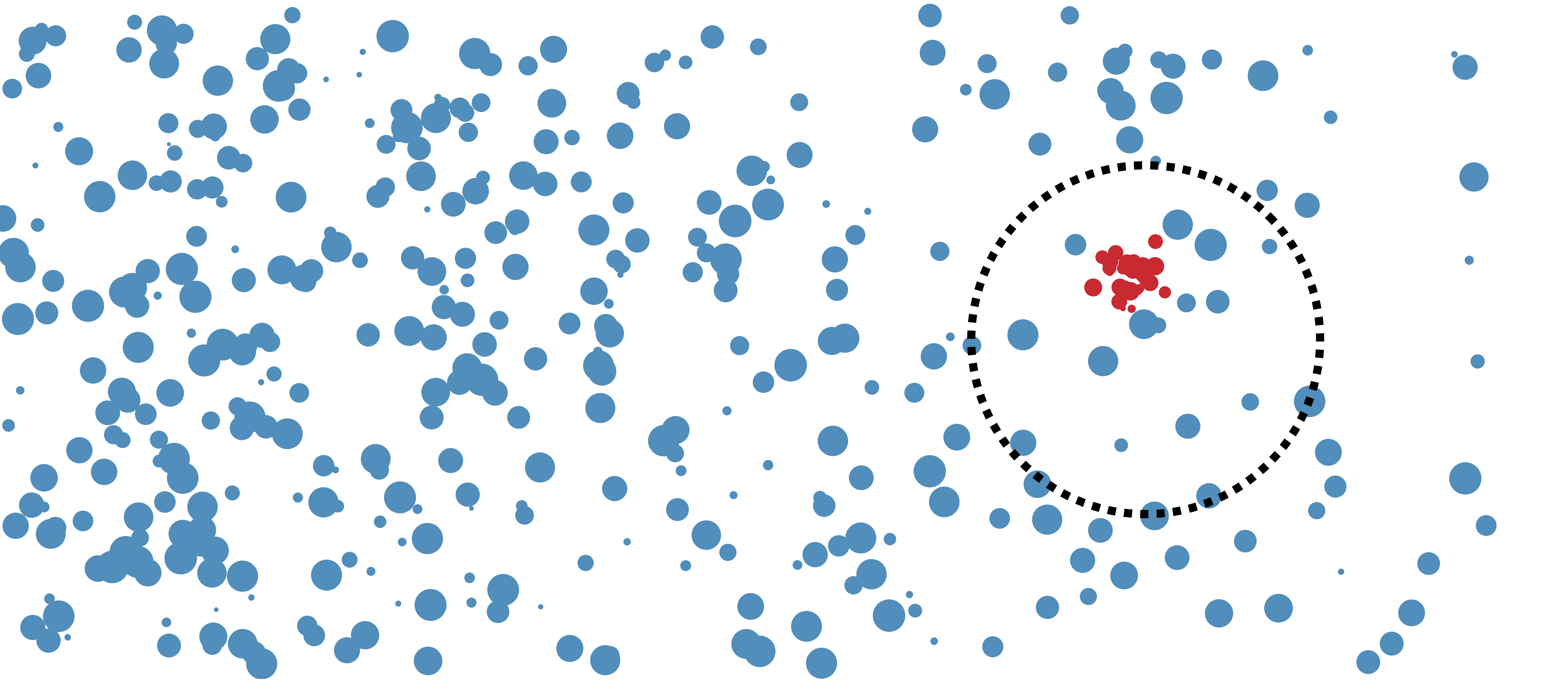

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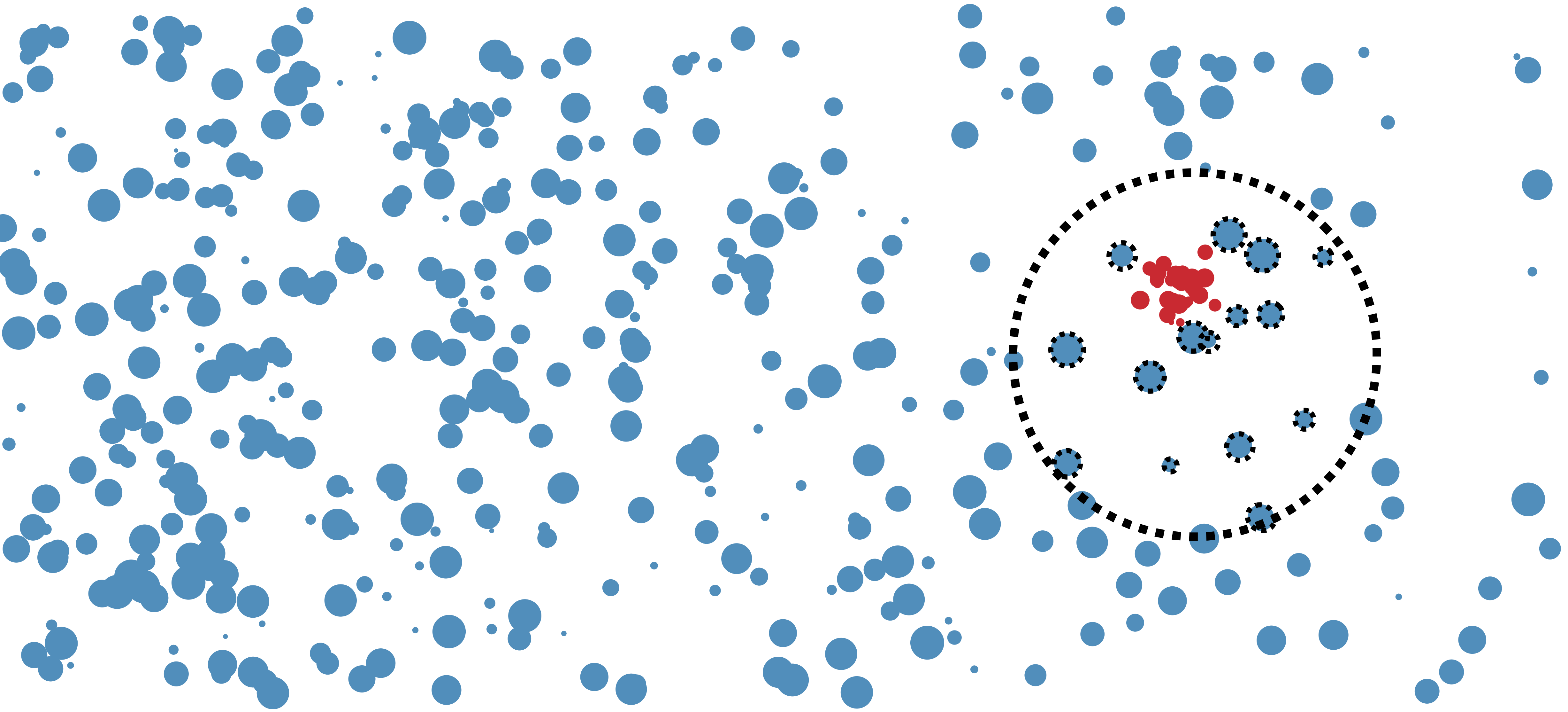

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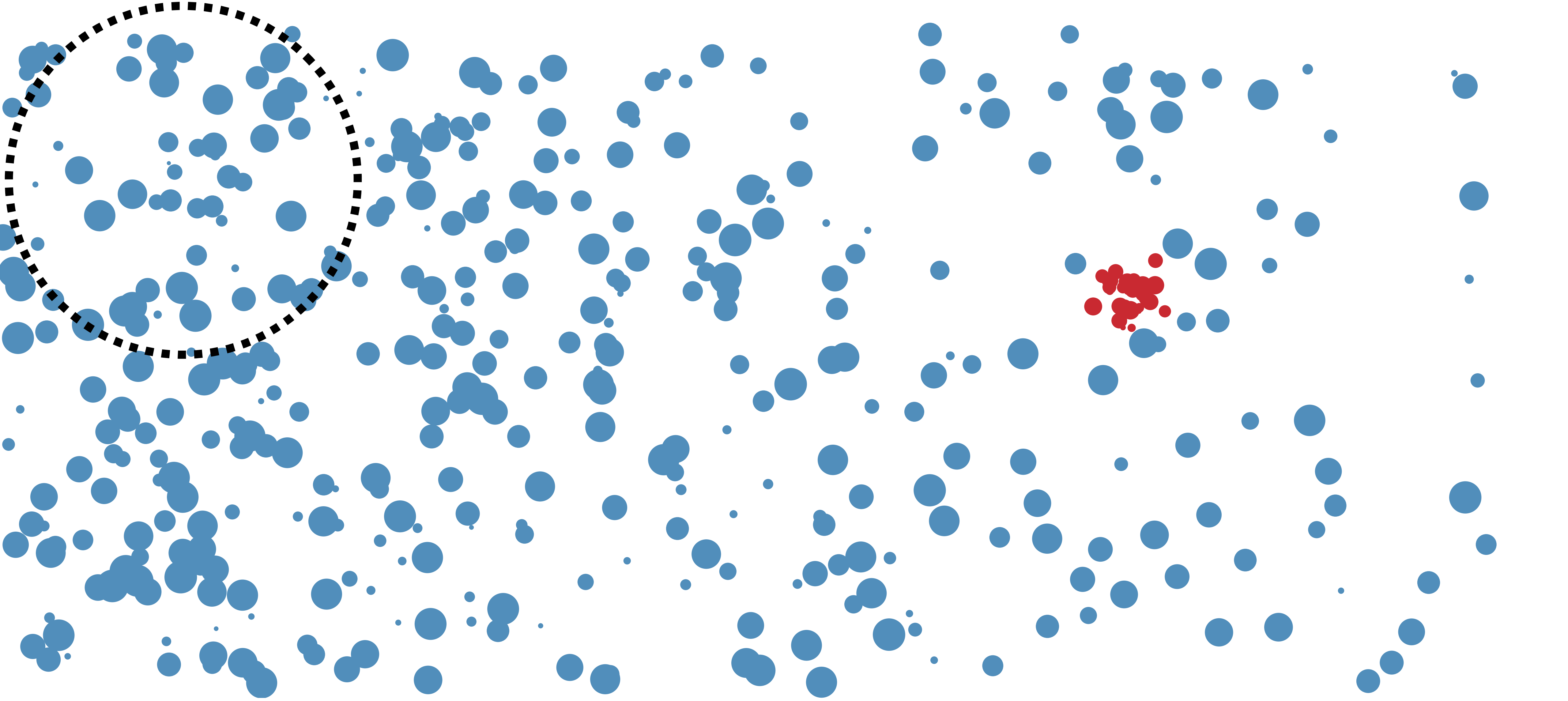

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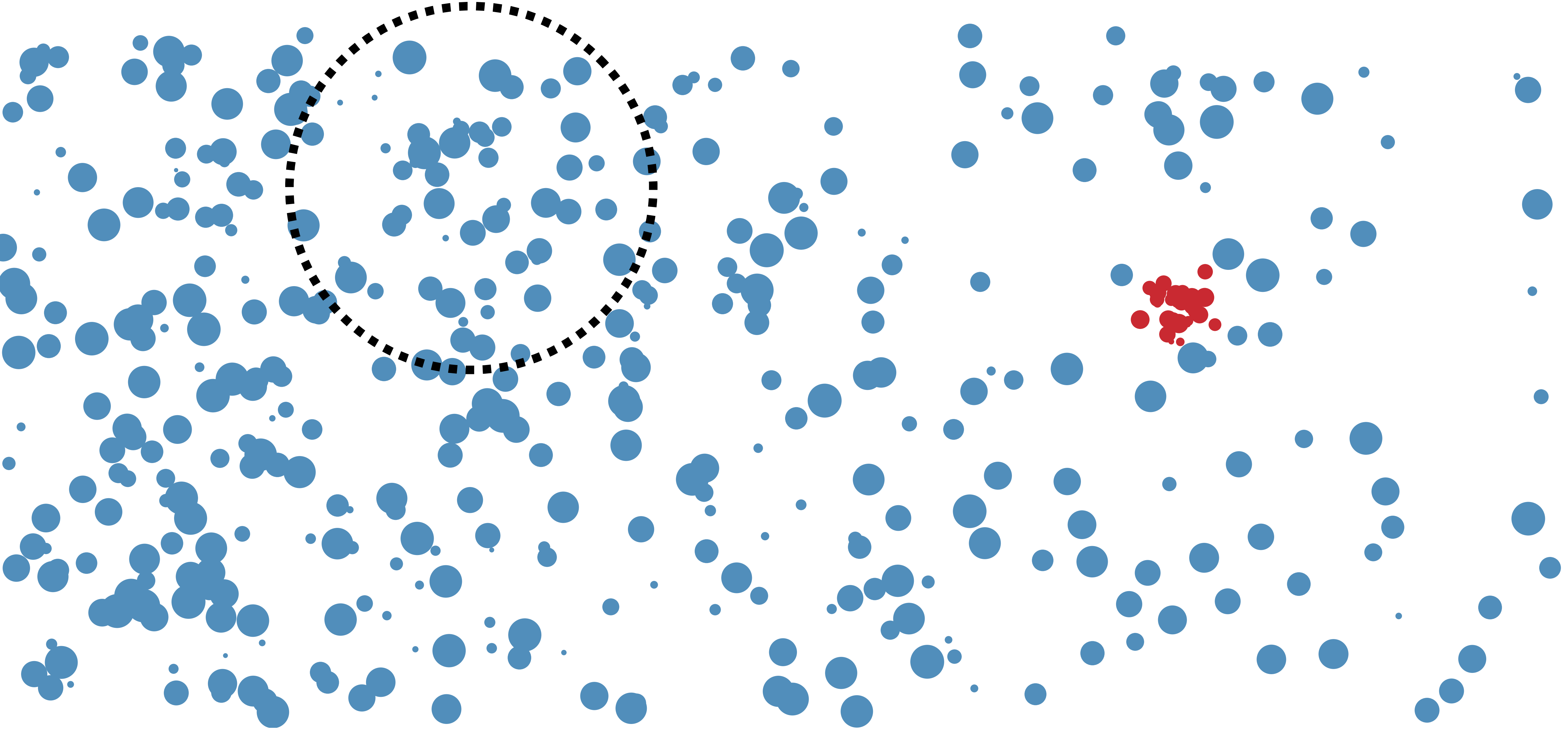

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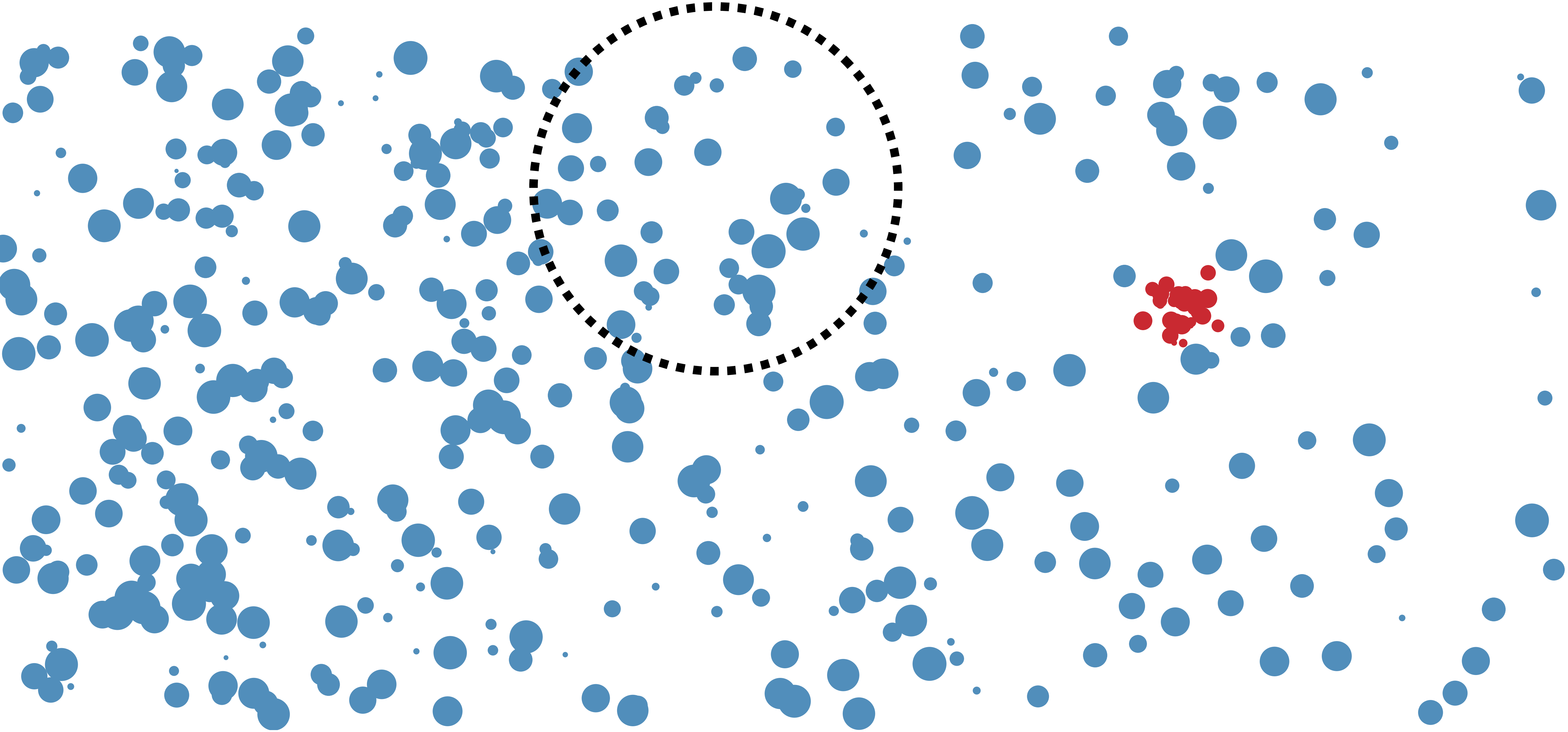
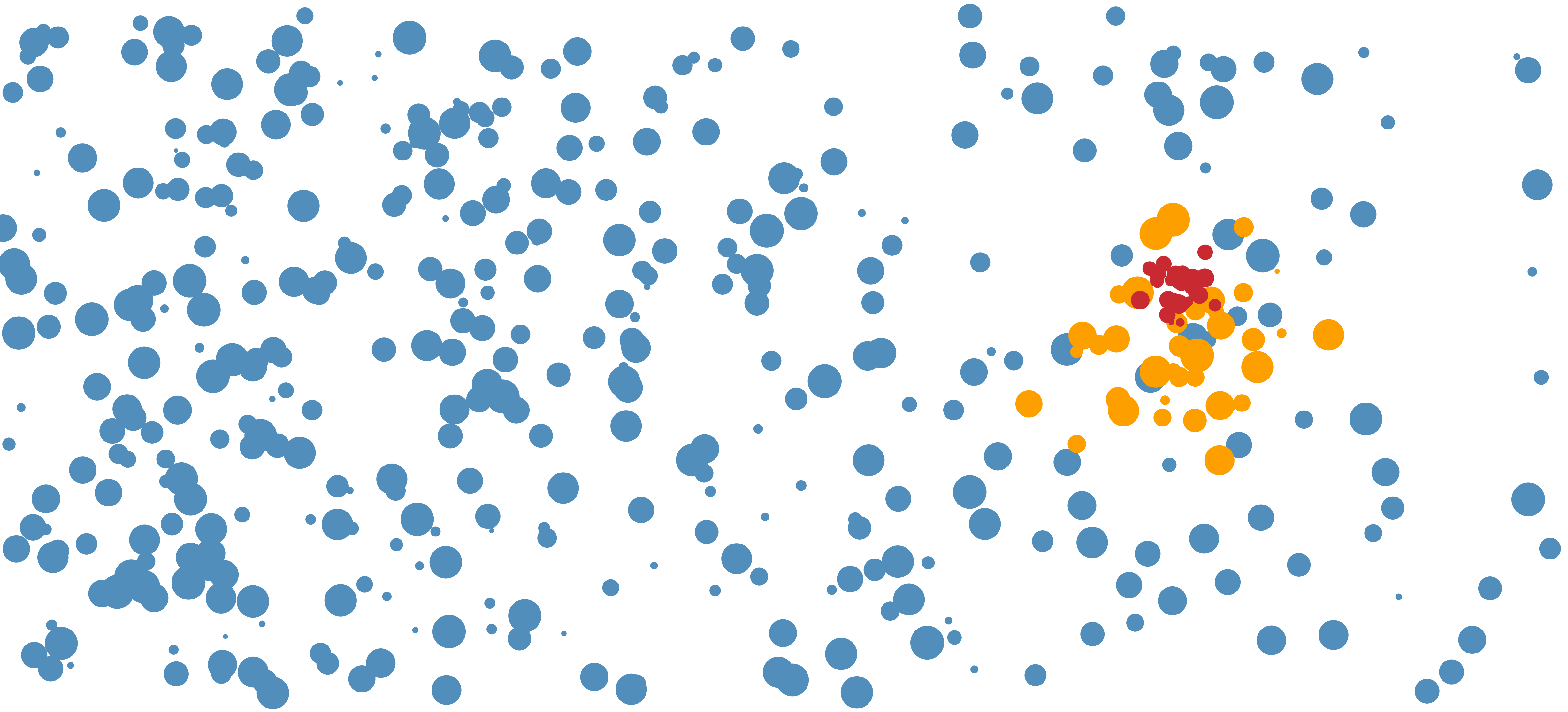


Finding an Anomaly in the Presence of a Known Signal



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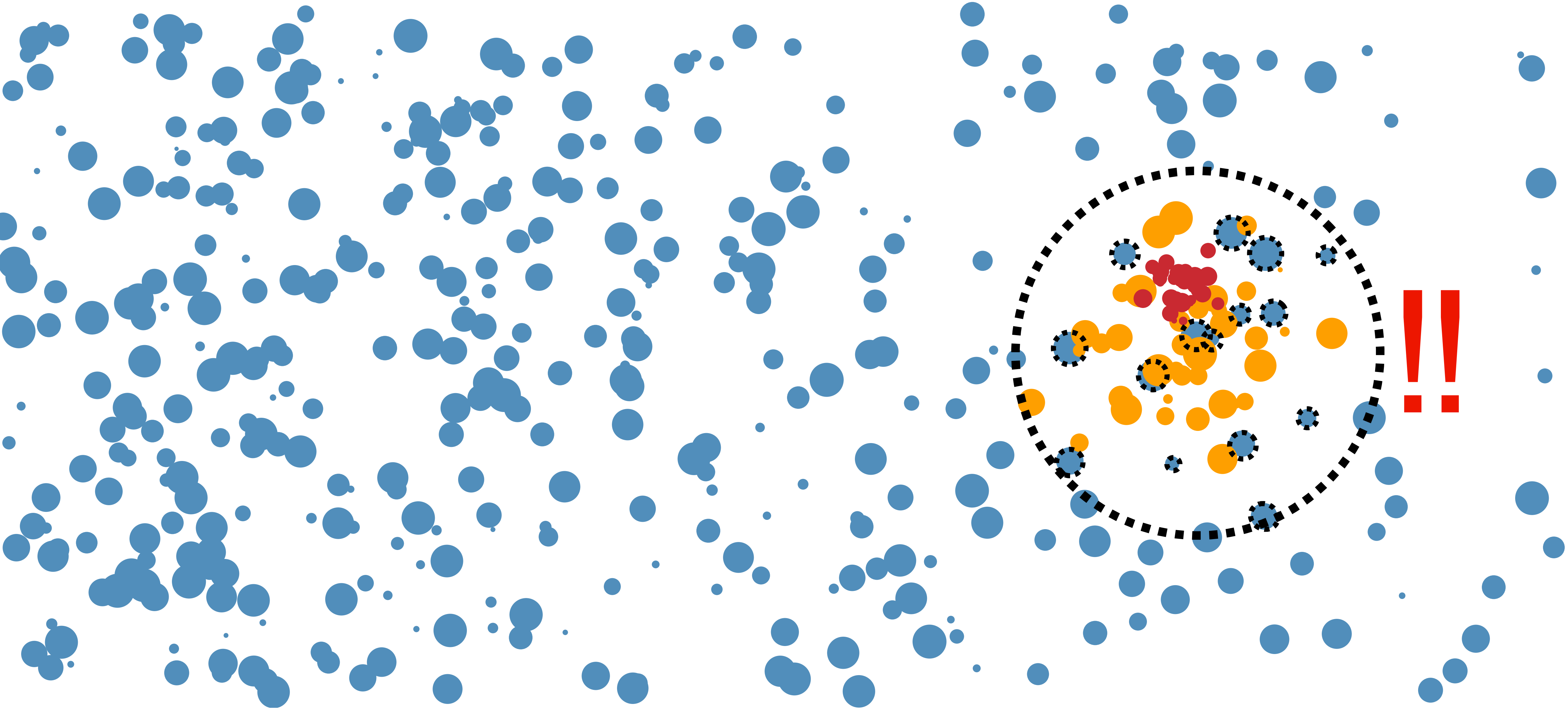

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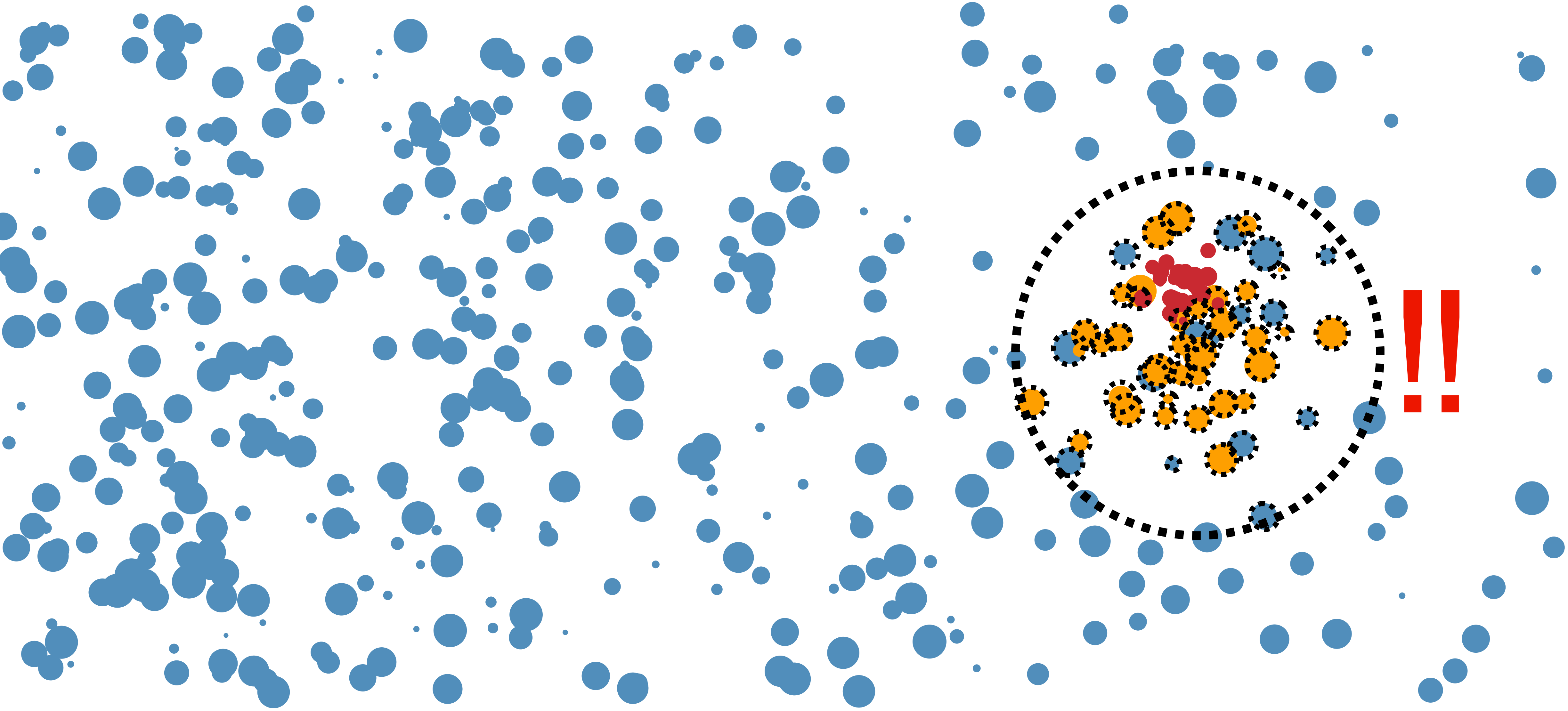
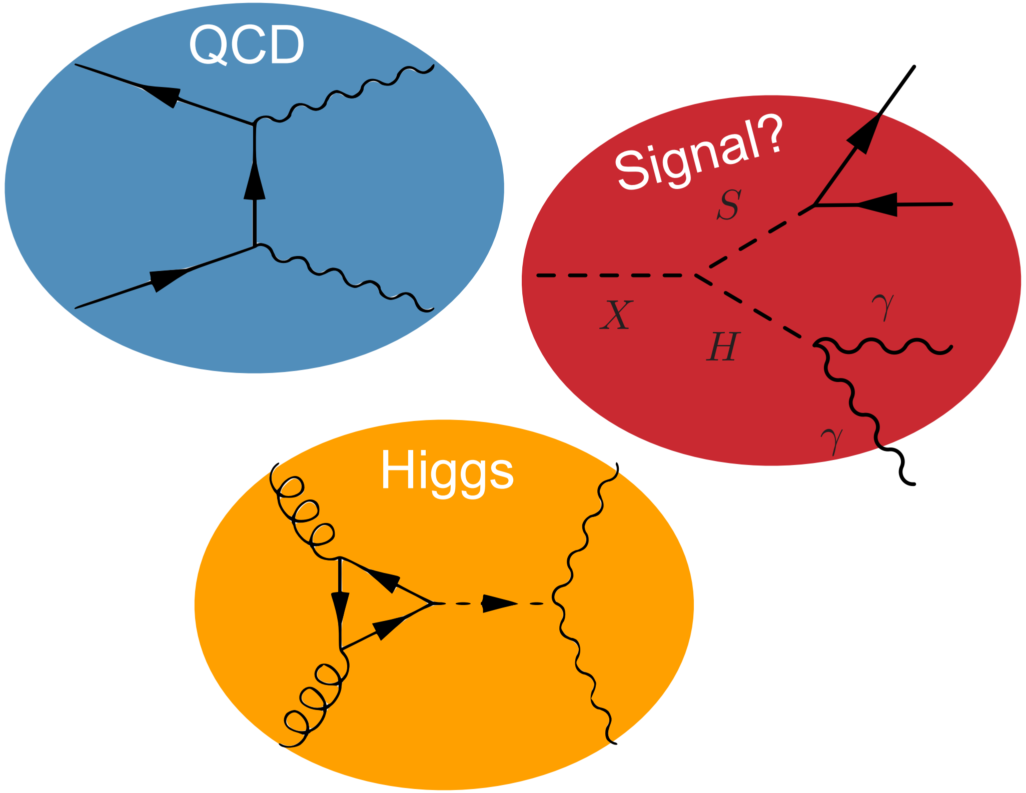


Use Information from Simulated Data!

HAXAD in a Nutshell

Find Anomalies of Higgs + X via ML-based Weakly Supervised Anomaly Detection



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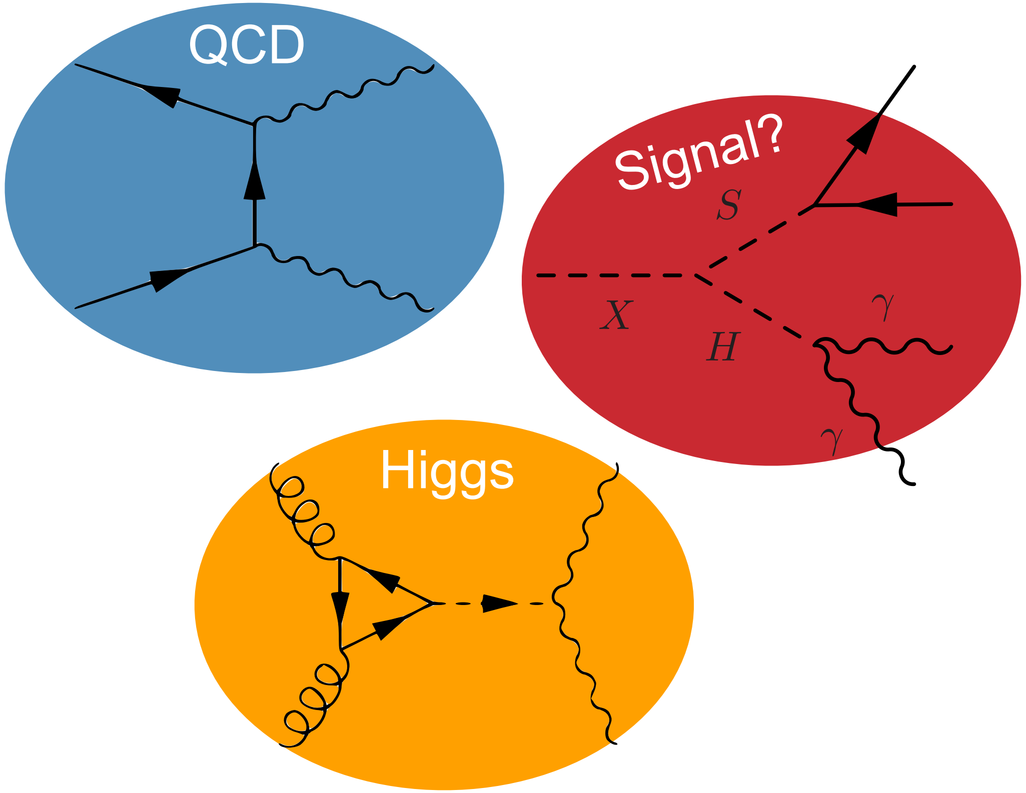

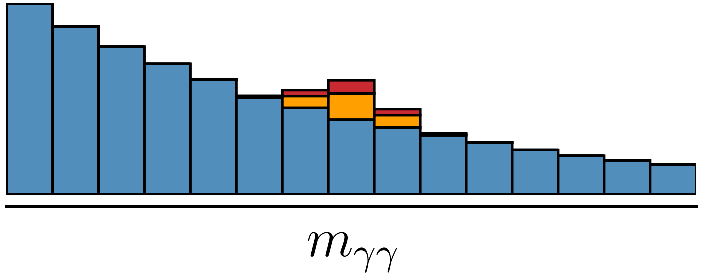

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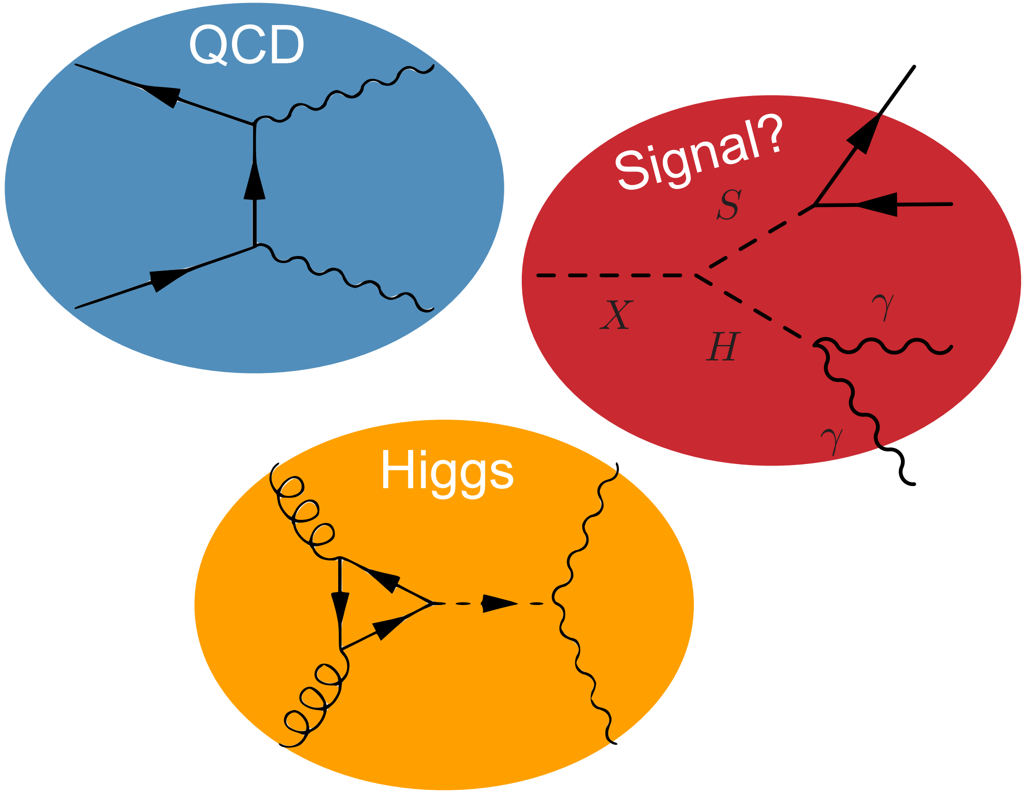

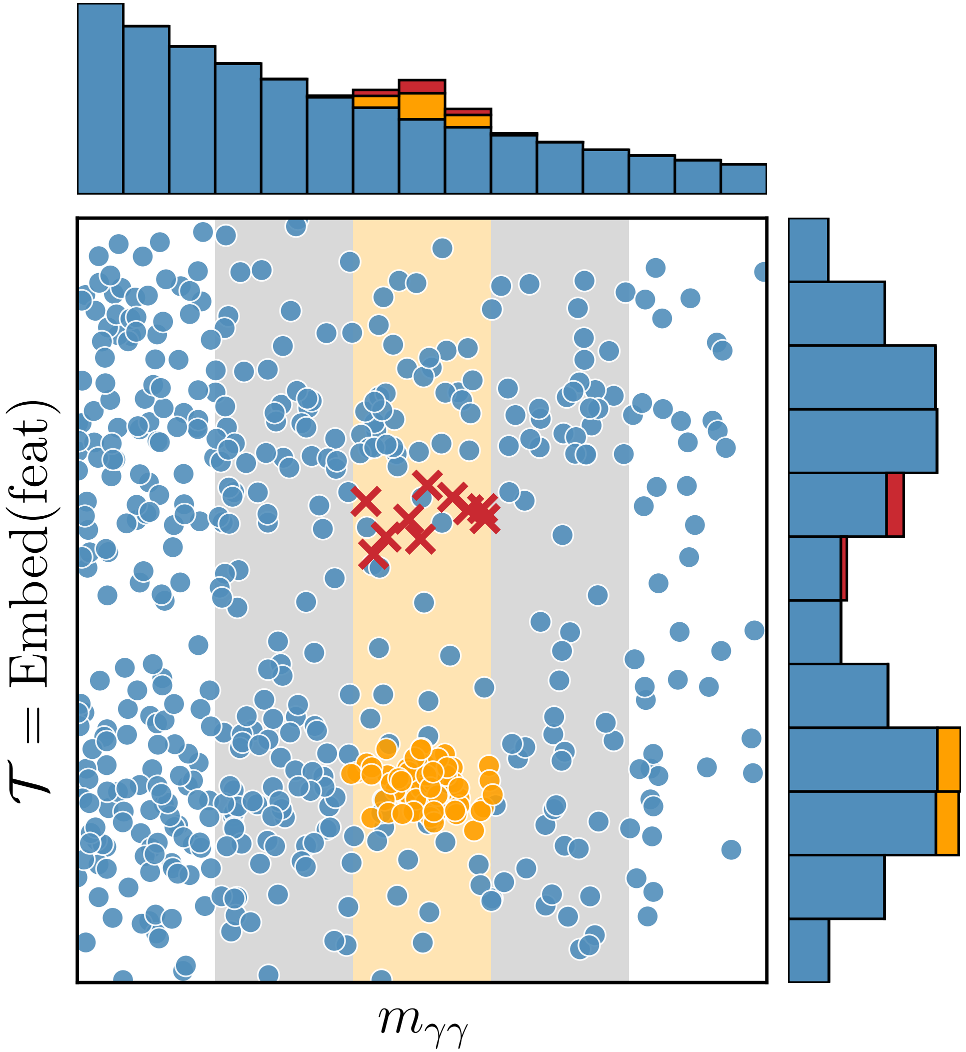

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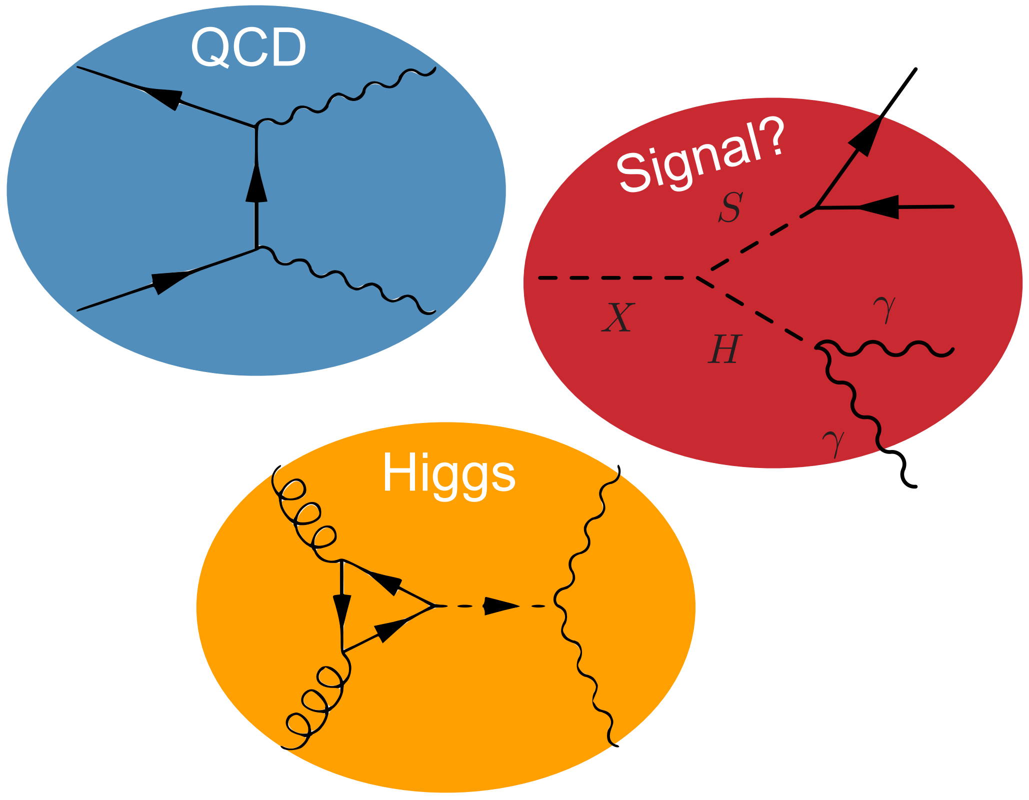

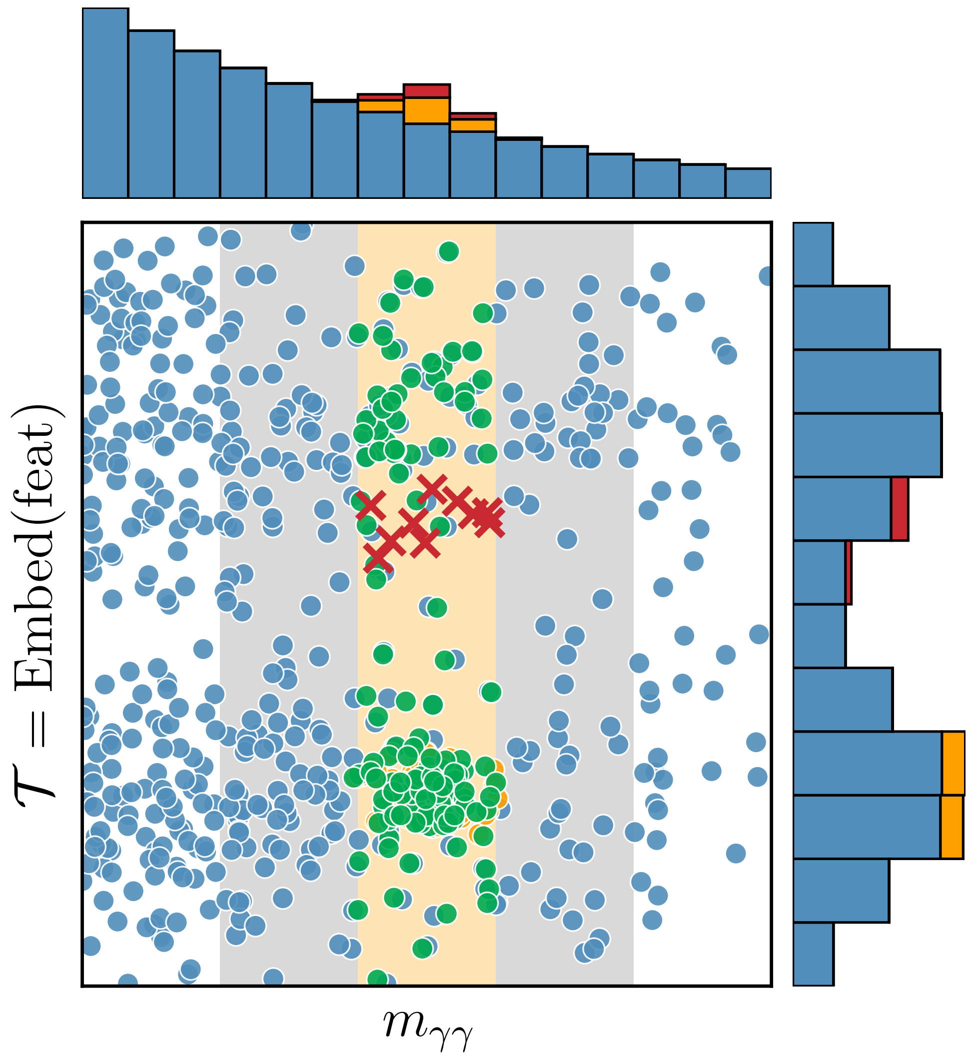

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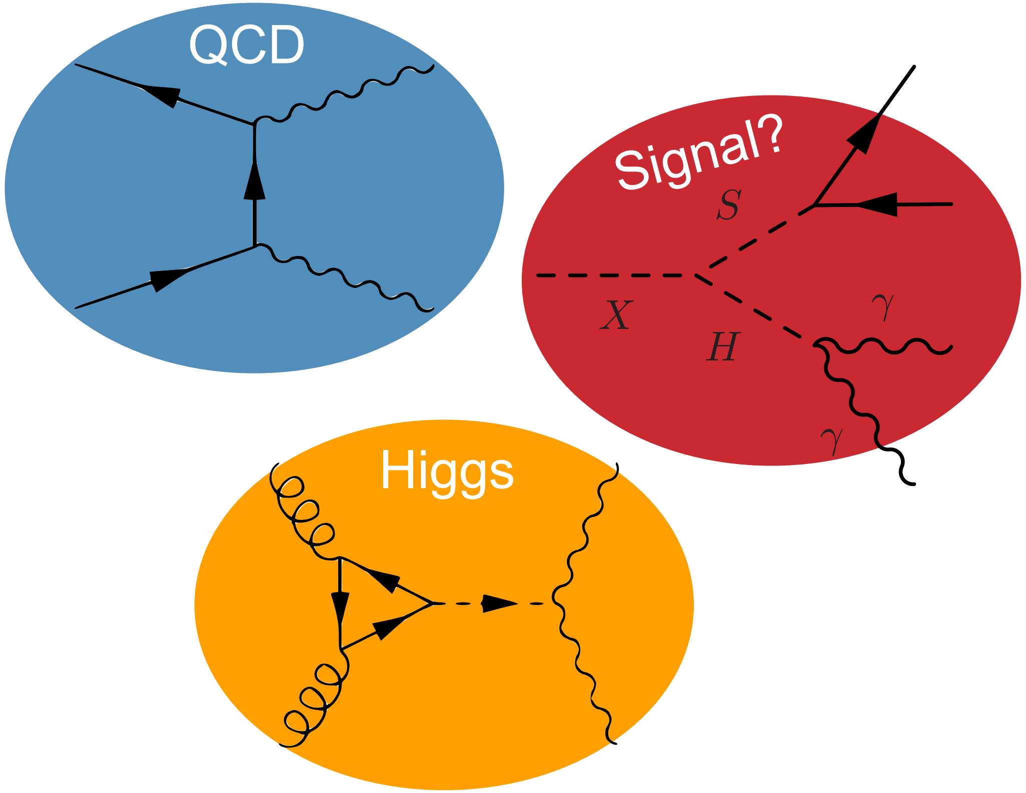

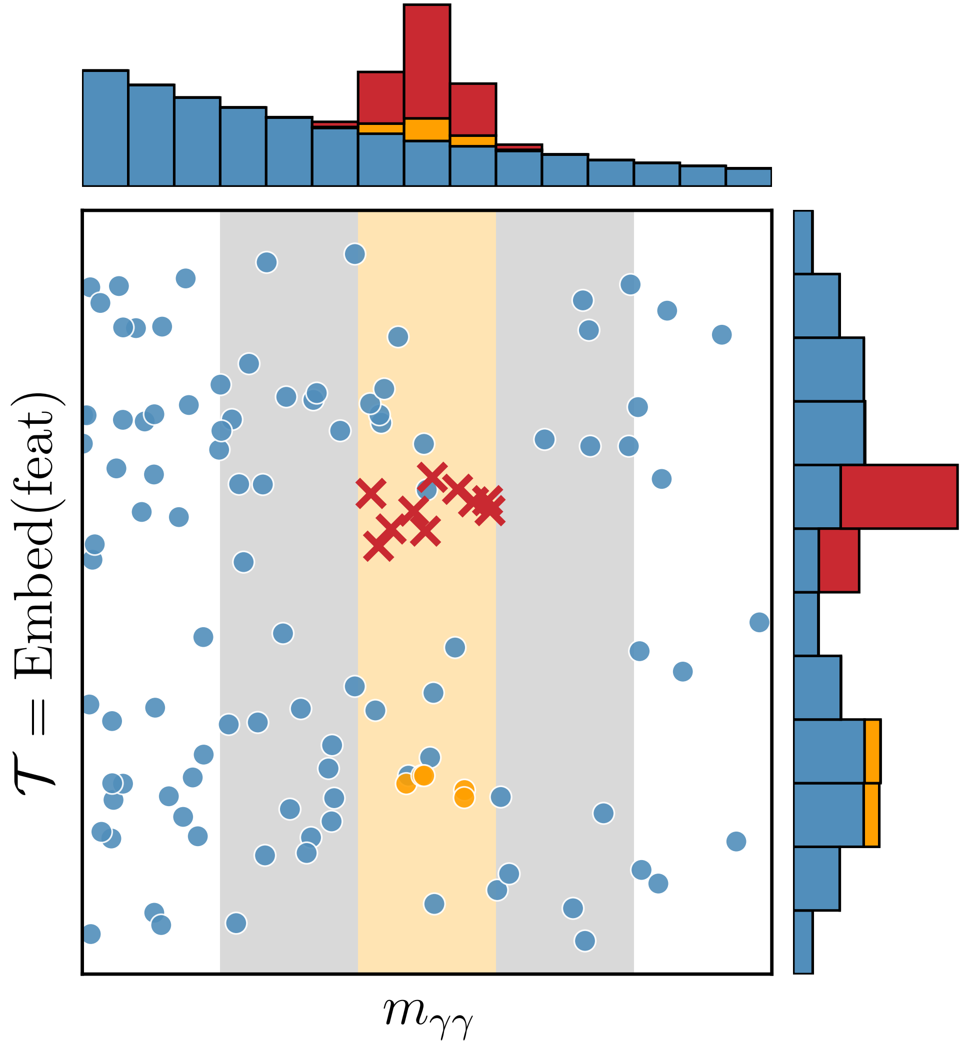

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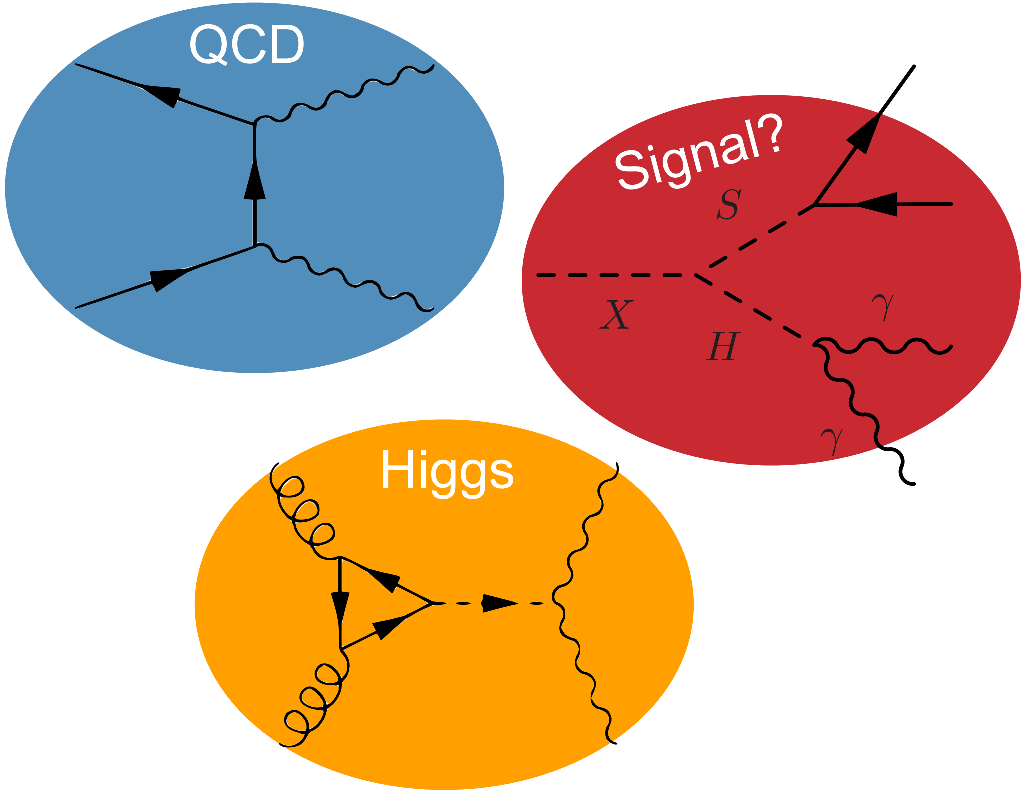
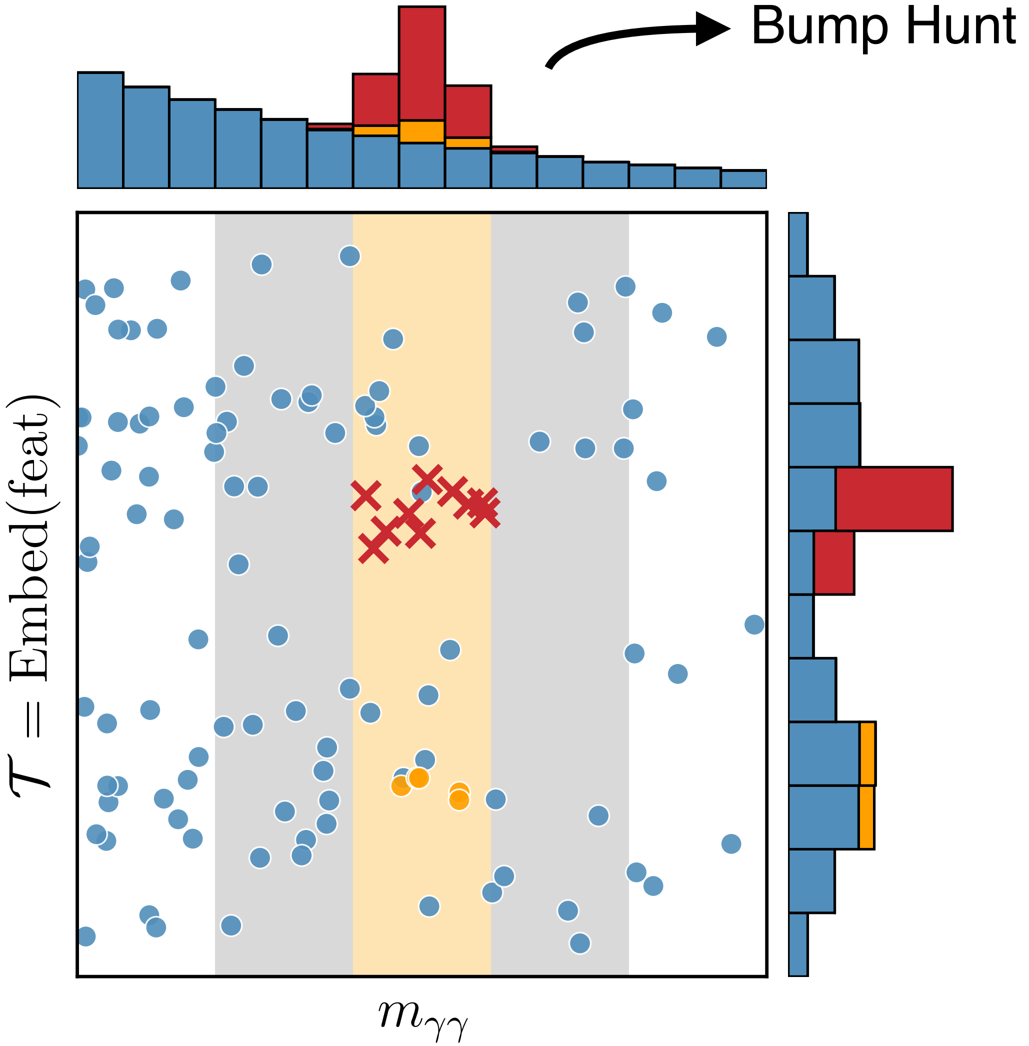


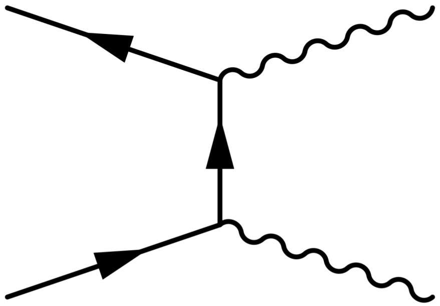


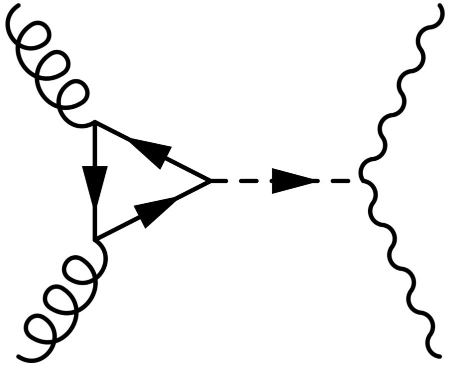
Simulated Dataset

- Generated with Madgraph + Pythia + Delphes using [EventGen Repository]
- Model approximated Run2 + Run3 luminosity 470 fb^{-1} (~ 2.1M events post pre-selection)

Backgrounds:

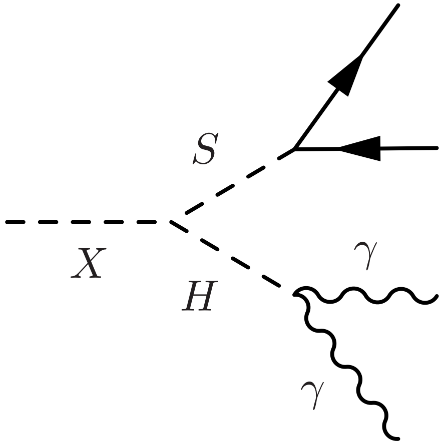
- Non-resonant: $\gamma\gamma$ + jets/leps/tt
- Resonant: Higgs (ggH, VBF, VH, ttH)





Signals:

- 12 signal models including: Extended Higgs sector, MSSM, FCNC, …
- Various mass points for each signal



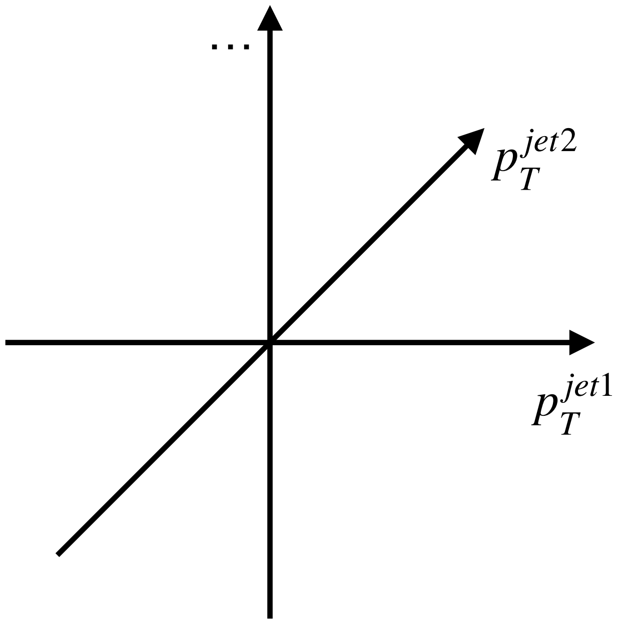
Many signatures with a Higgs in the final state…

Everything is easier in the right Latent Space

2603.25794

Feature Space

- High-dimensional ~O(100)
- Unregularized, missing values
- Exhaustive



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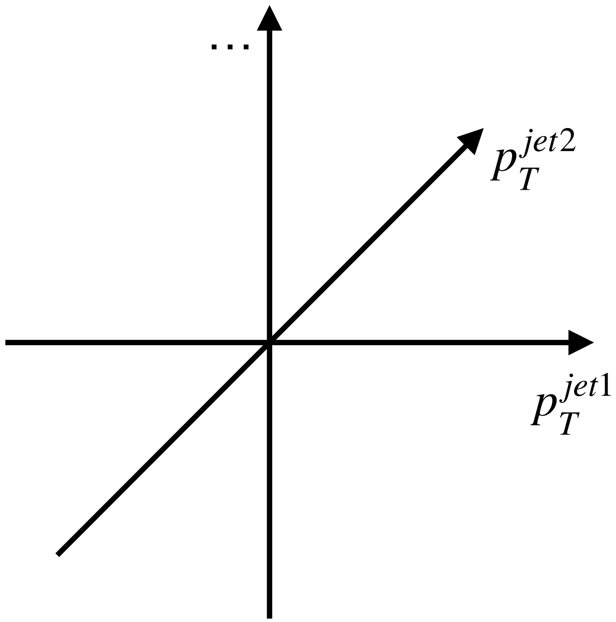
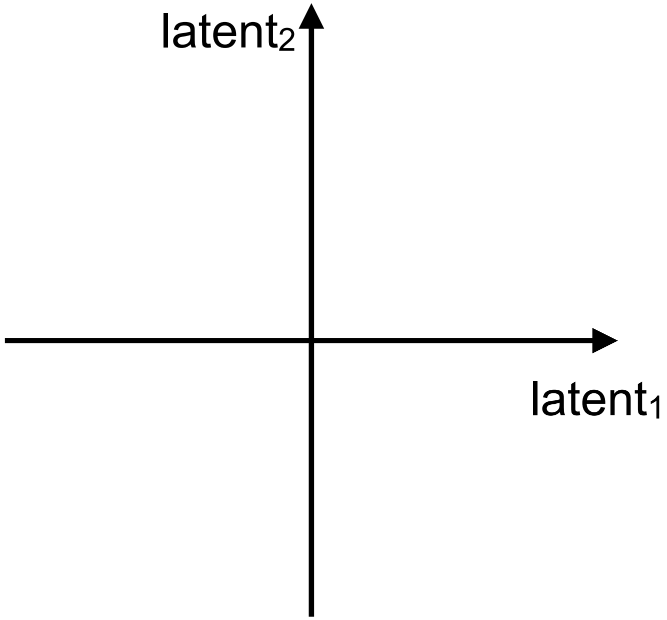


Embedding Model (2 options)

Latent Space

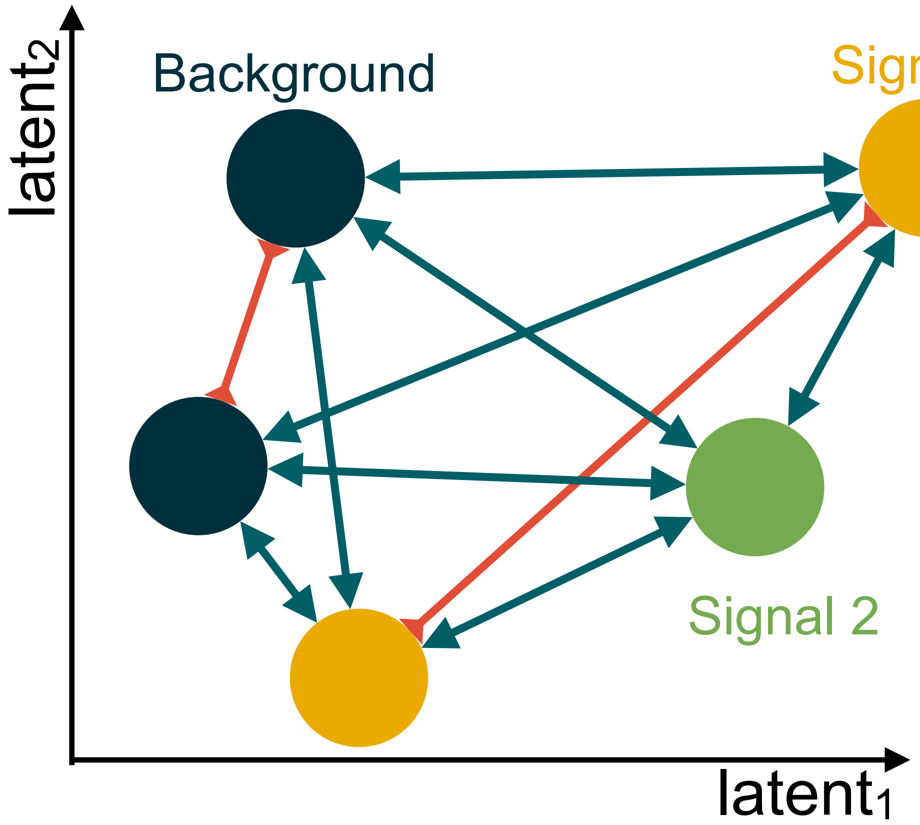
- Low-dimensional ~O(10)
- Regularized (e.g. Gaussian)
- Signal sensitive



Semi-Supervised Embedding: Contrastive Learning 1

2603.25794

- Using contrastive loss (*SupCon*) to embed events:
  - Same process close together
  - Different process far apart
- Ensure processes have Gaussian shape (easy to model with background estimation)



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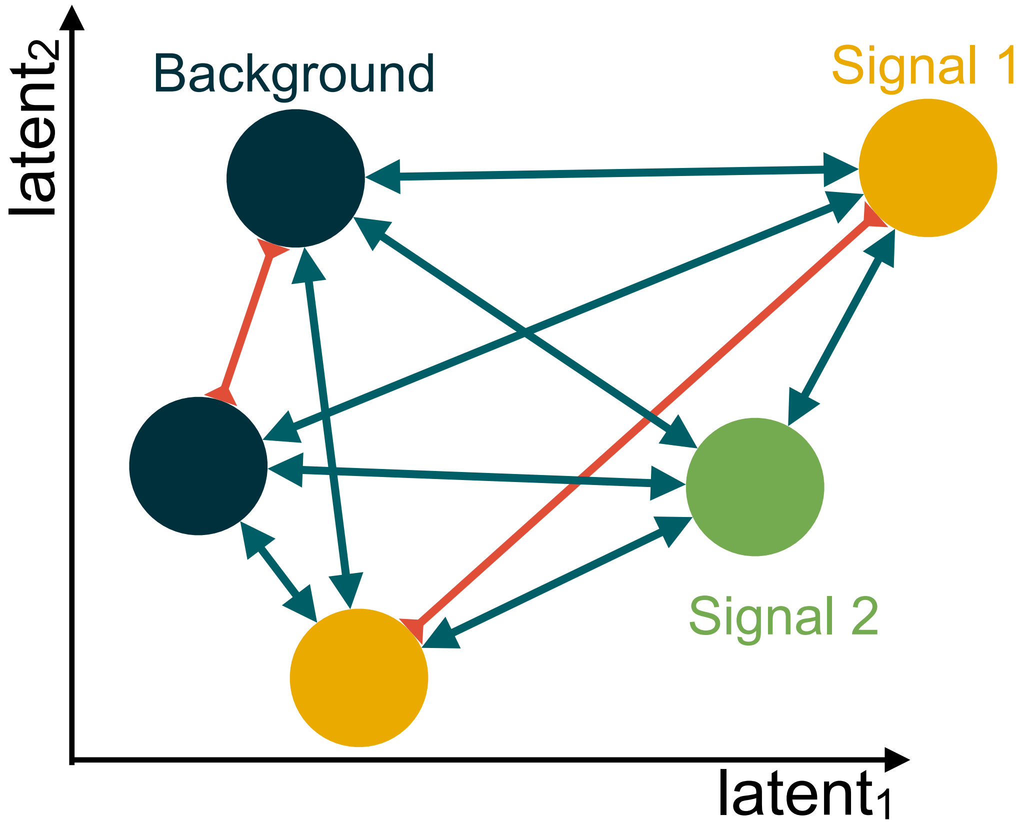
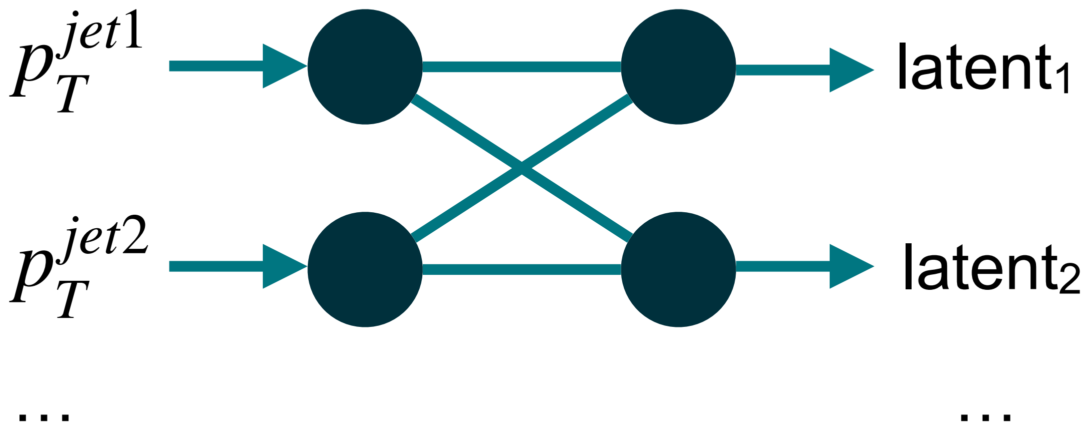
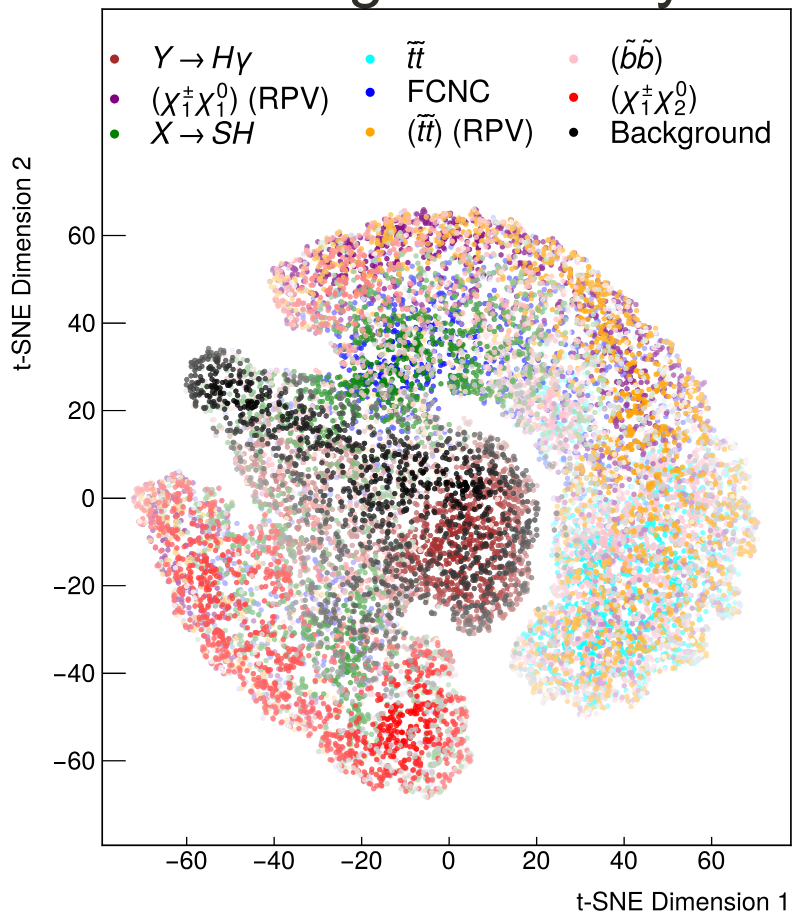




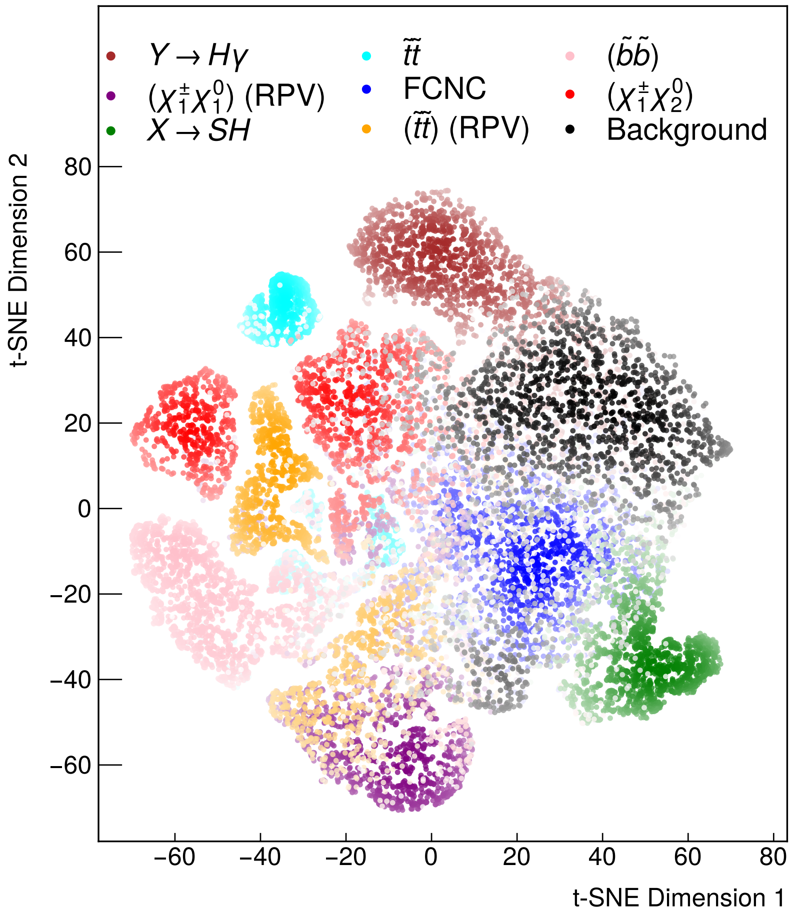
Semi-Supervised Embedding: Contrastive Learning 2

- Training with signal samples forms the latent space
- Inter-/extrapolates to unseen signals

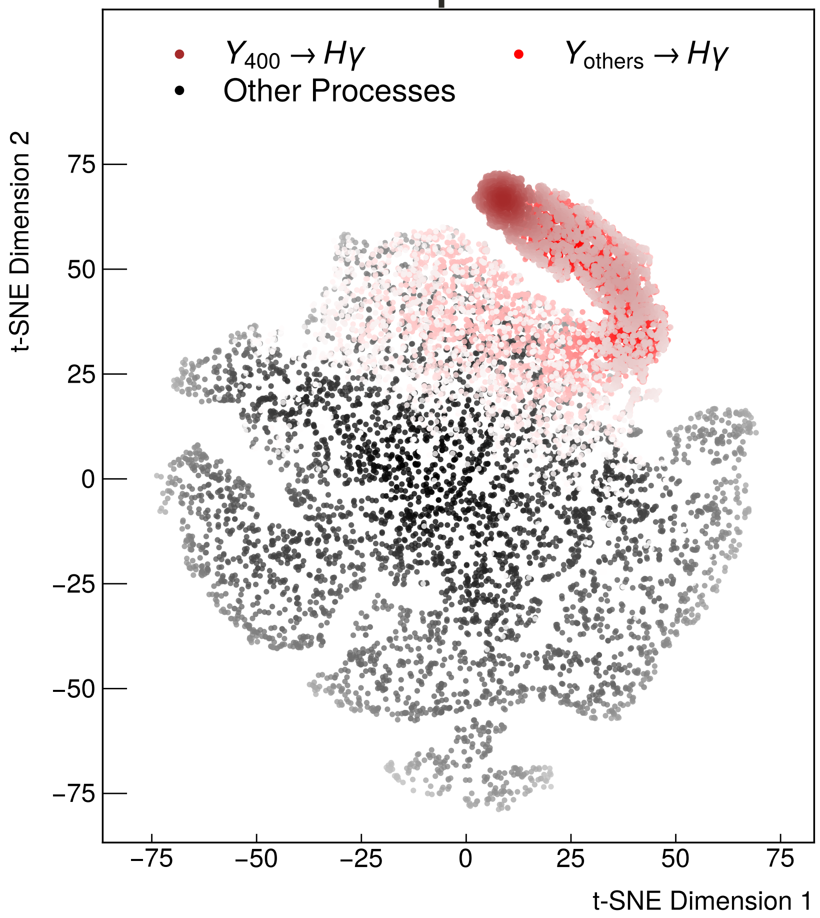
Background-only



In-dataset

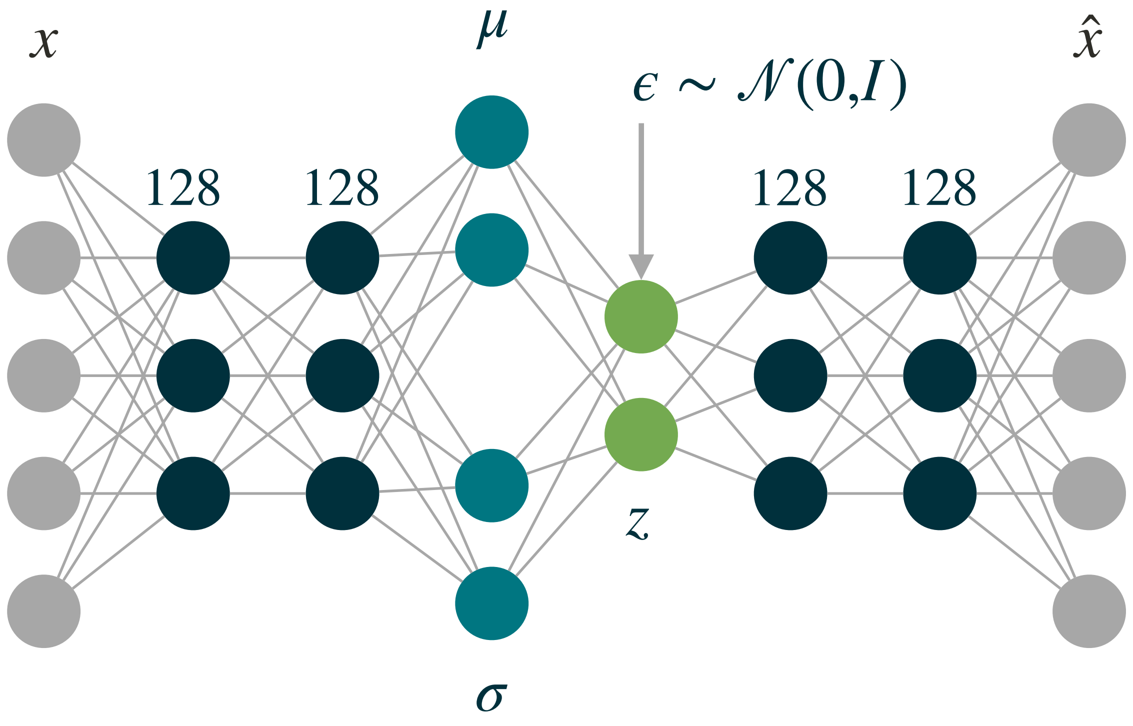


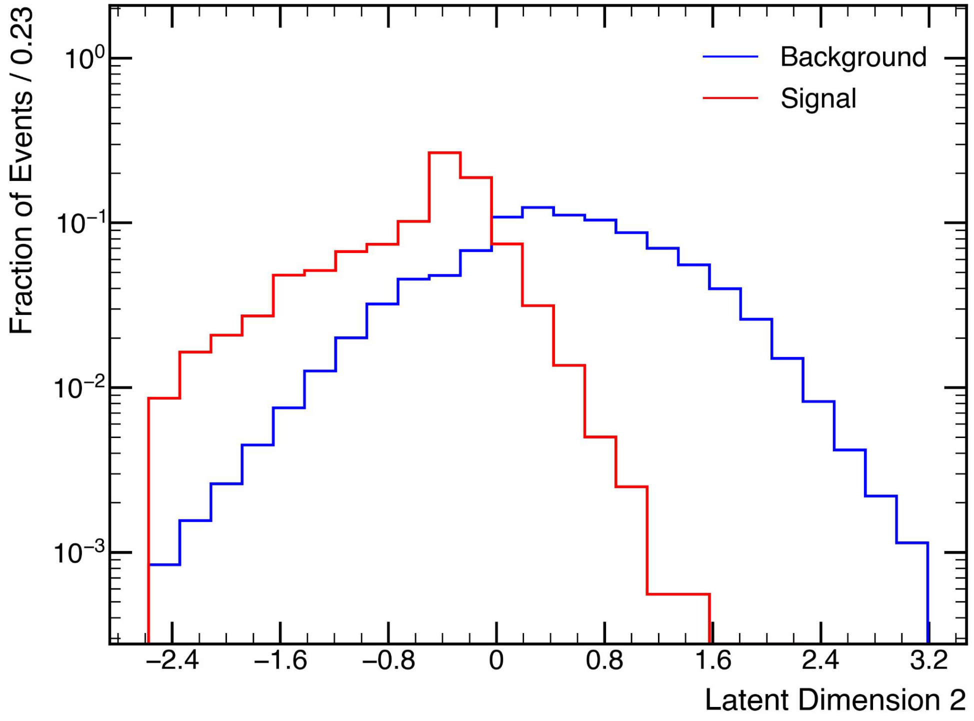
Interpolation



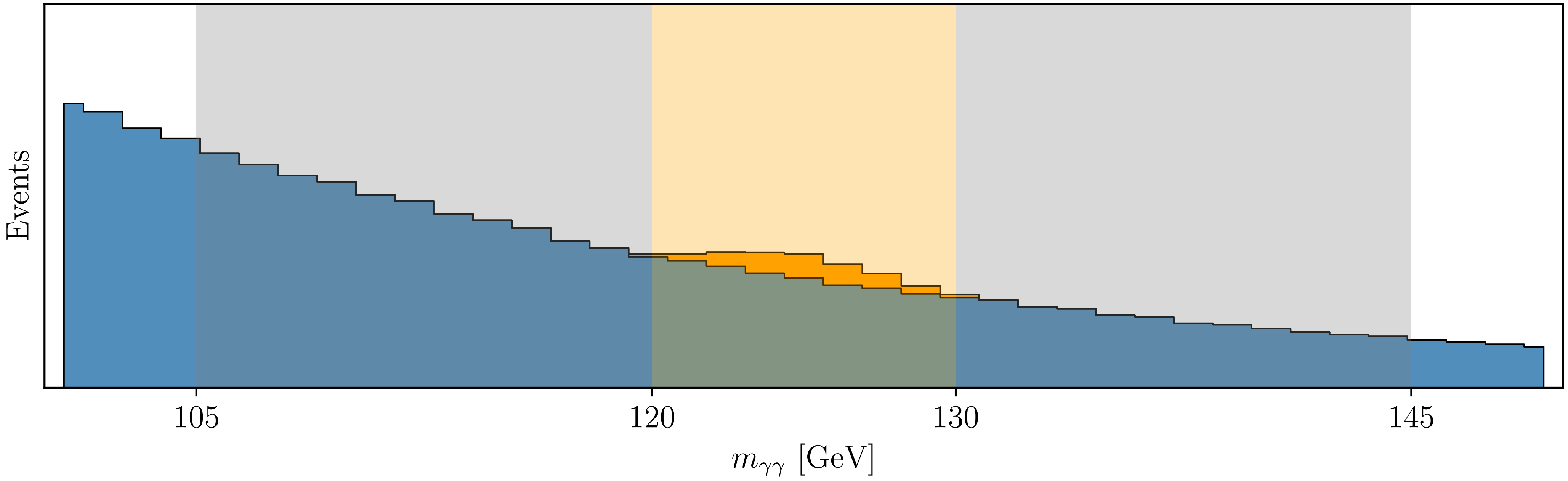
Unsupervised Embedding: Variational Autoencoder

- Variational Autoencoder (40k params.) with **19 input features (x)** and **7 latent features (z)**
- Trained with simulated background events (non-resonant and resonant)
- Completely signal-agnostic and still sensitive to many signals





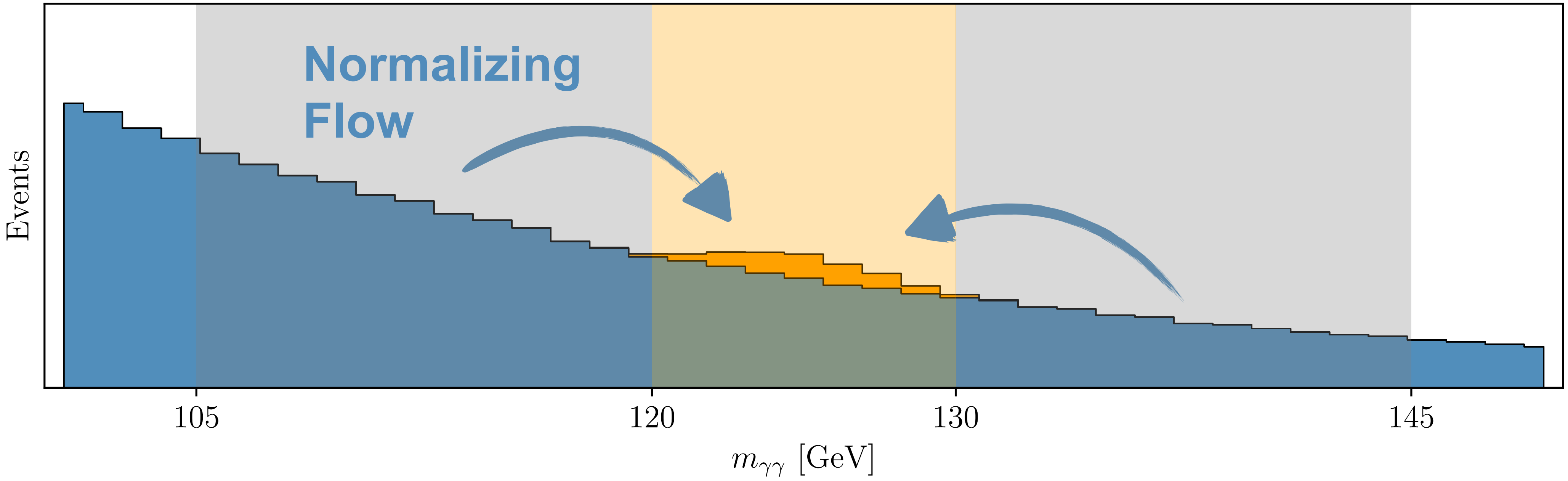
Background Estimation



Background Estimation

Non-resonant

- Signal rare in the sidebands (SB)
- Train normalizing flow models in latent space SB and interpolate to signal region (SR)



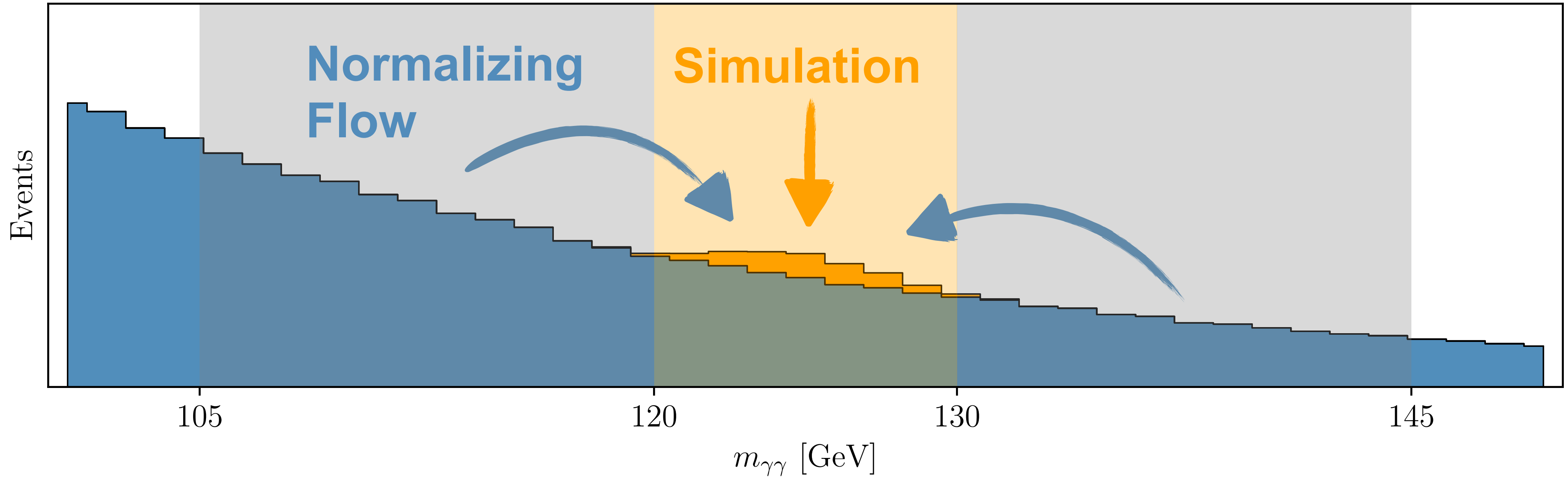
Background Estimation

Non-resonant

- Signal rare in the sidebands (SB)
- Train normalizing flow models in latent space SB and interpolate to signal region (SR)

Resonant

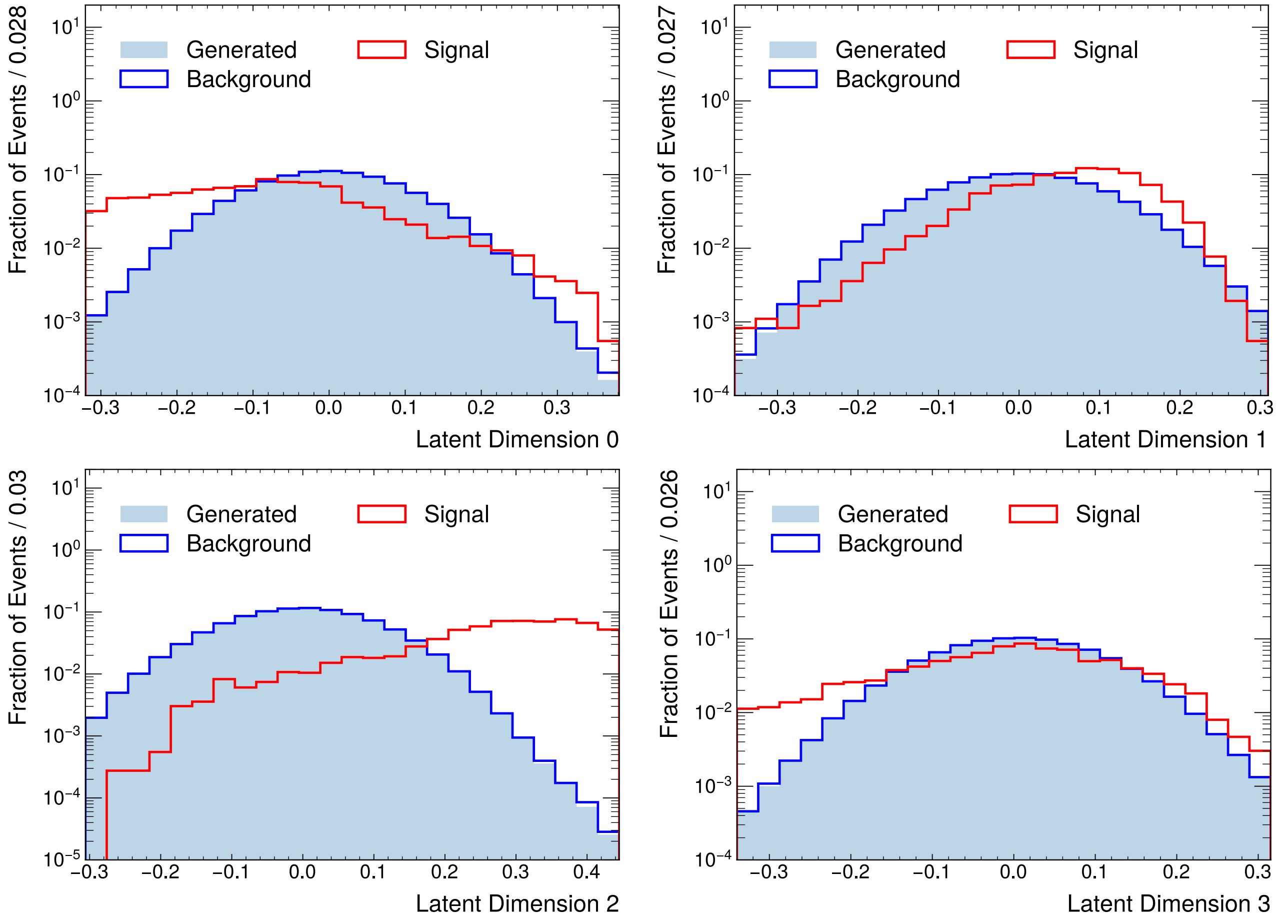
- High-quality Higgs simulation available
- Directly use simulated SM Higgs events encoded in latent space



Successful Background Estimation in Both Latent Spaces

Semi-supervised (100→6)

[Stronger discrimination]



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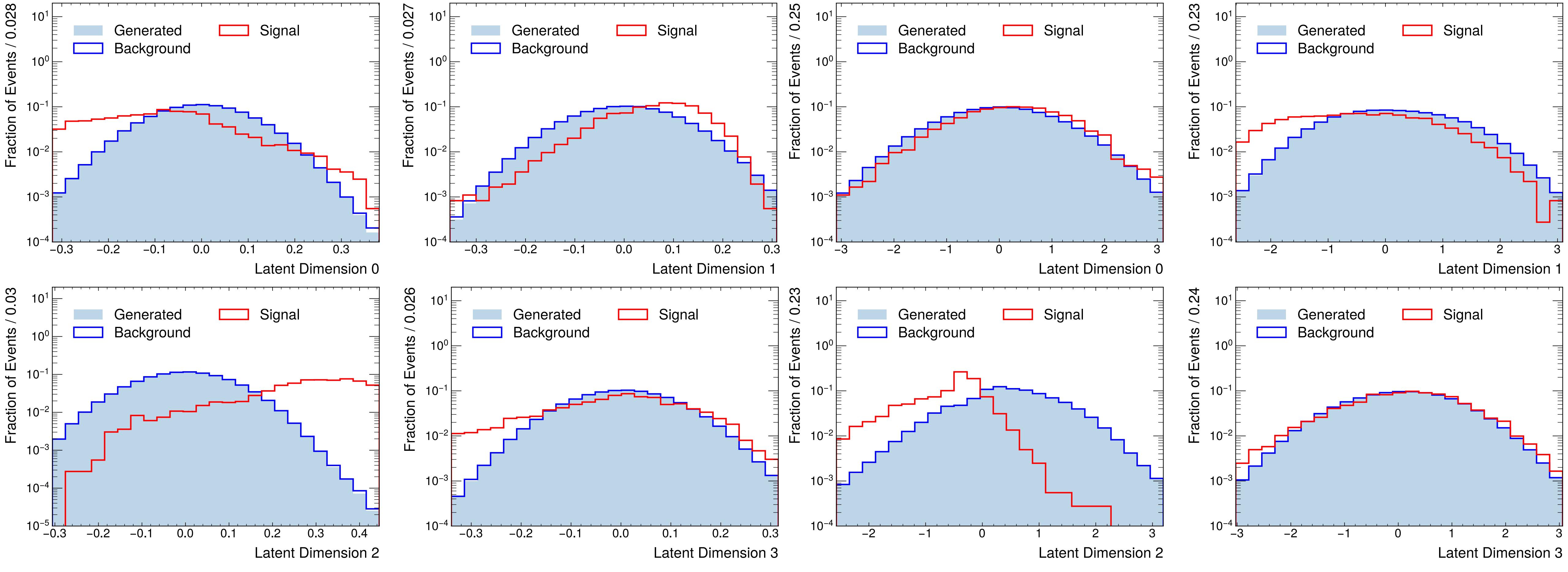
Successful Background Estimation in Both Latent Spaces

Semi-supervised (100→6)

[Stronger discrimination]

Unsupervised (19→7)

[can be more general]



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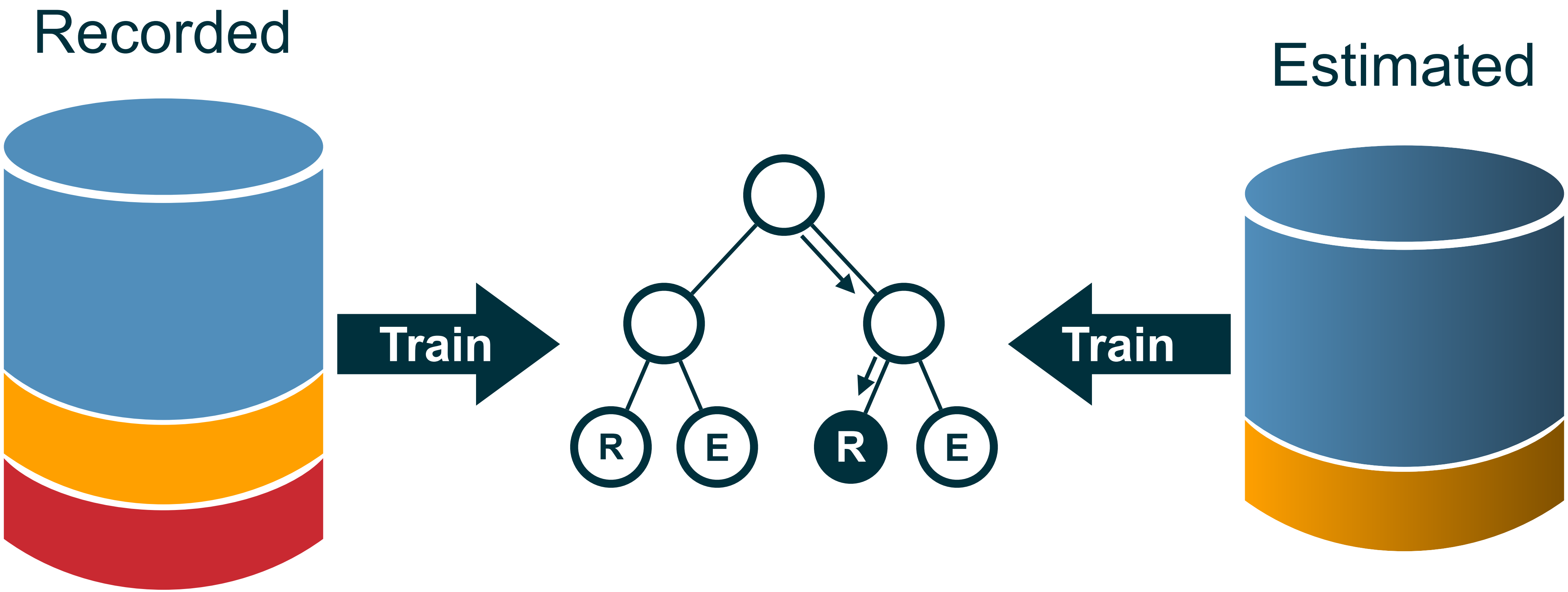
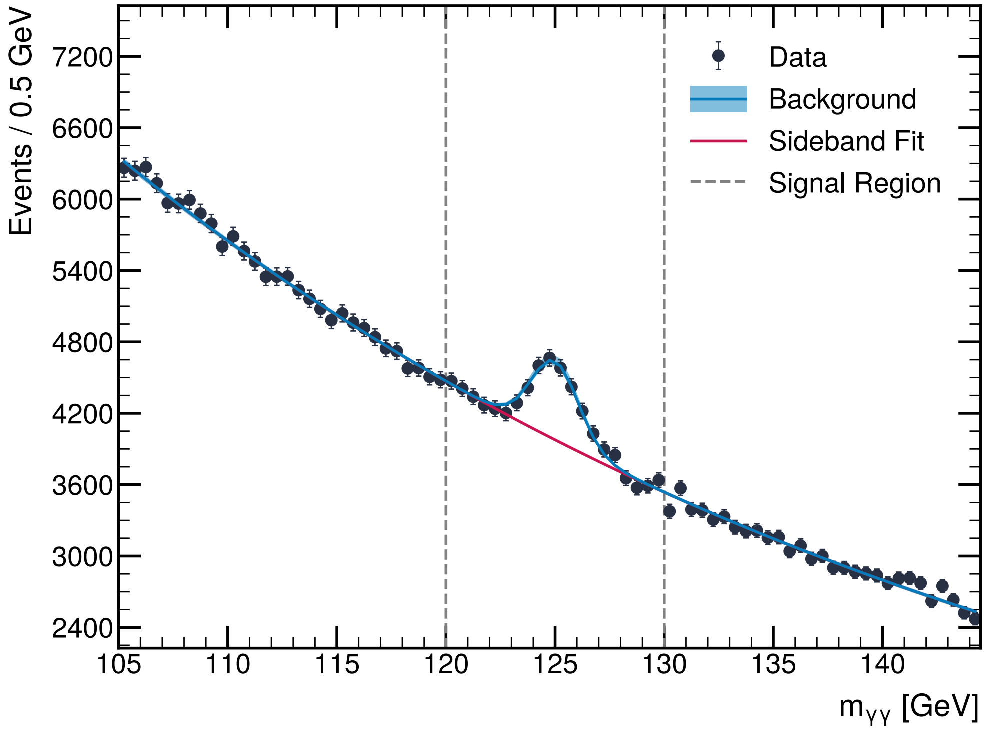
...

Train Classification for an Arbitrary Anomaly

- Classification without Labels (CWoLa) via Boosted Decision Tree Ensembles
- Ensemble of multiple BDTs per spectrum (sensitivity), ensemble of multiple spectra (stability)
- Keep 0.5% of the events

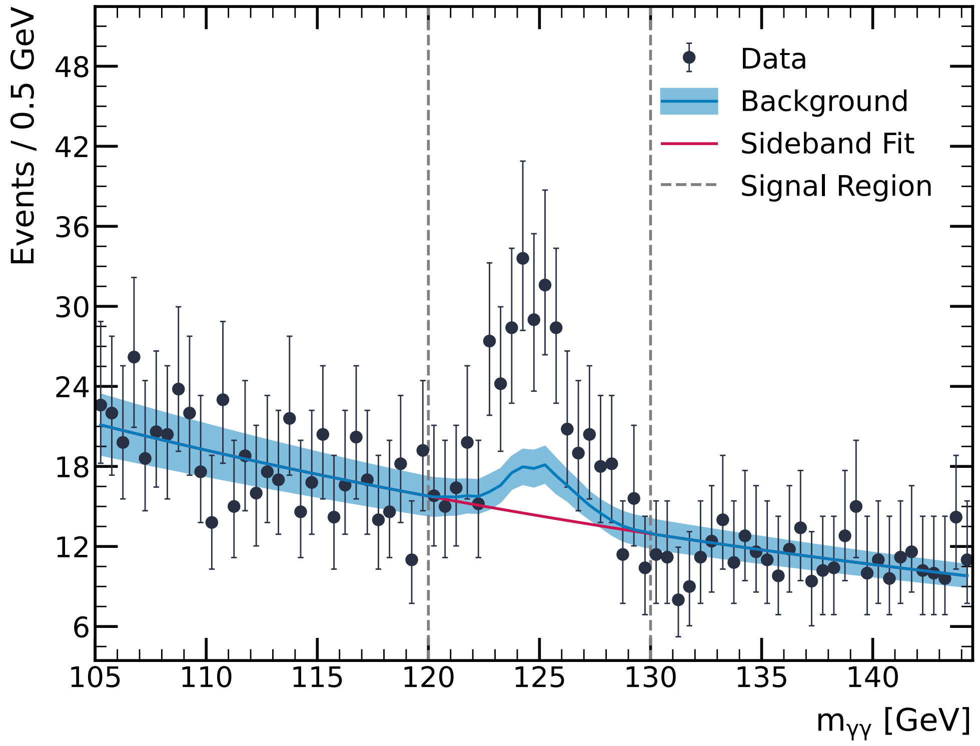


Inference


Events / 0.5 GeV
7200
6600
6000
5400
4800
4200
3600
3000
2400
105
110
115
120
125
130
135
140
$m_{\gamma\gamma}$ [GeV]
Data
Background
Sideband Fit
Signal Region

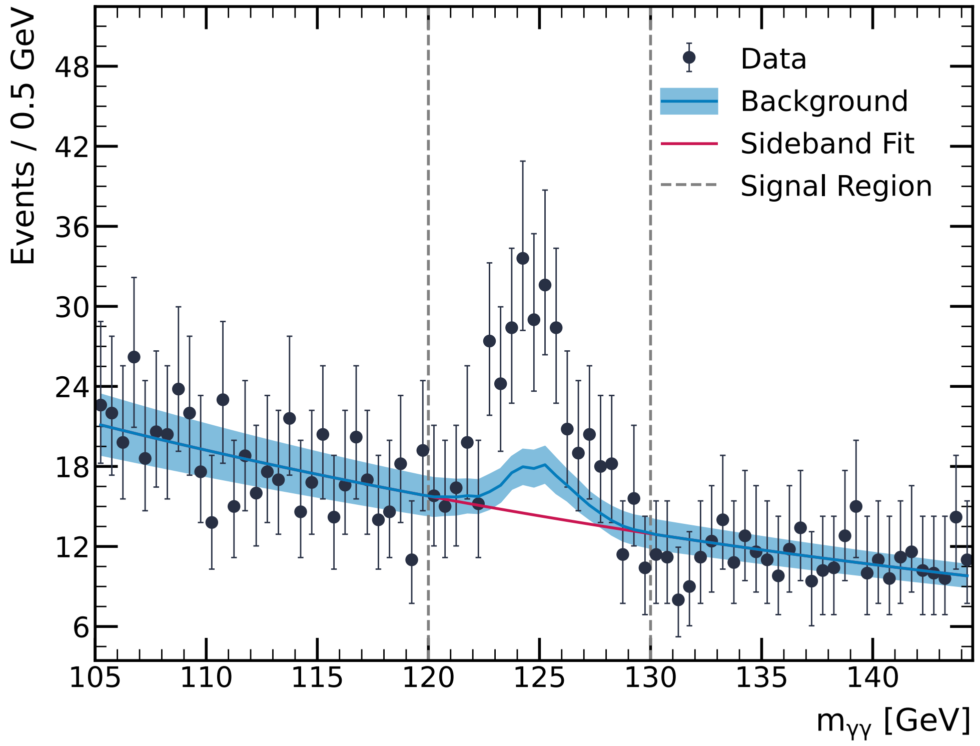
Inference

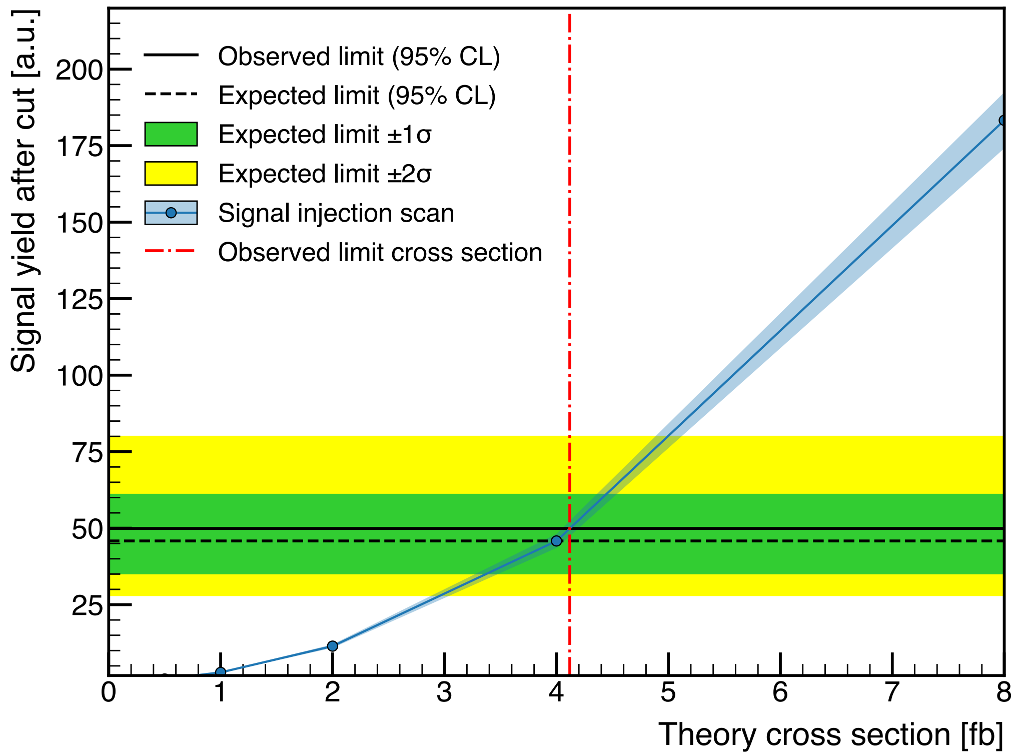
- Cut makes anomaly visible and highly significant



Inference

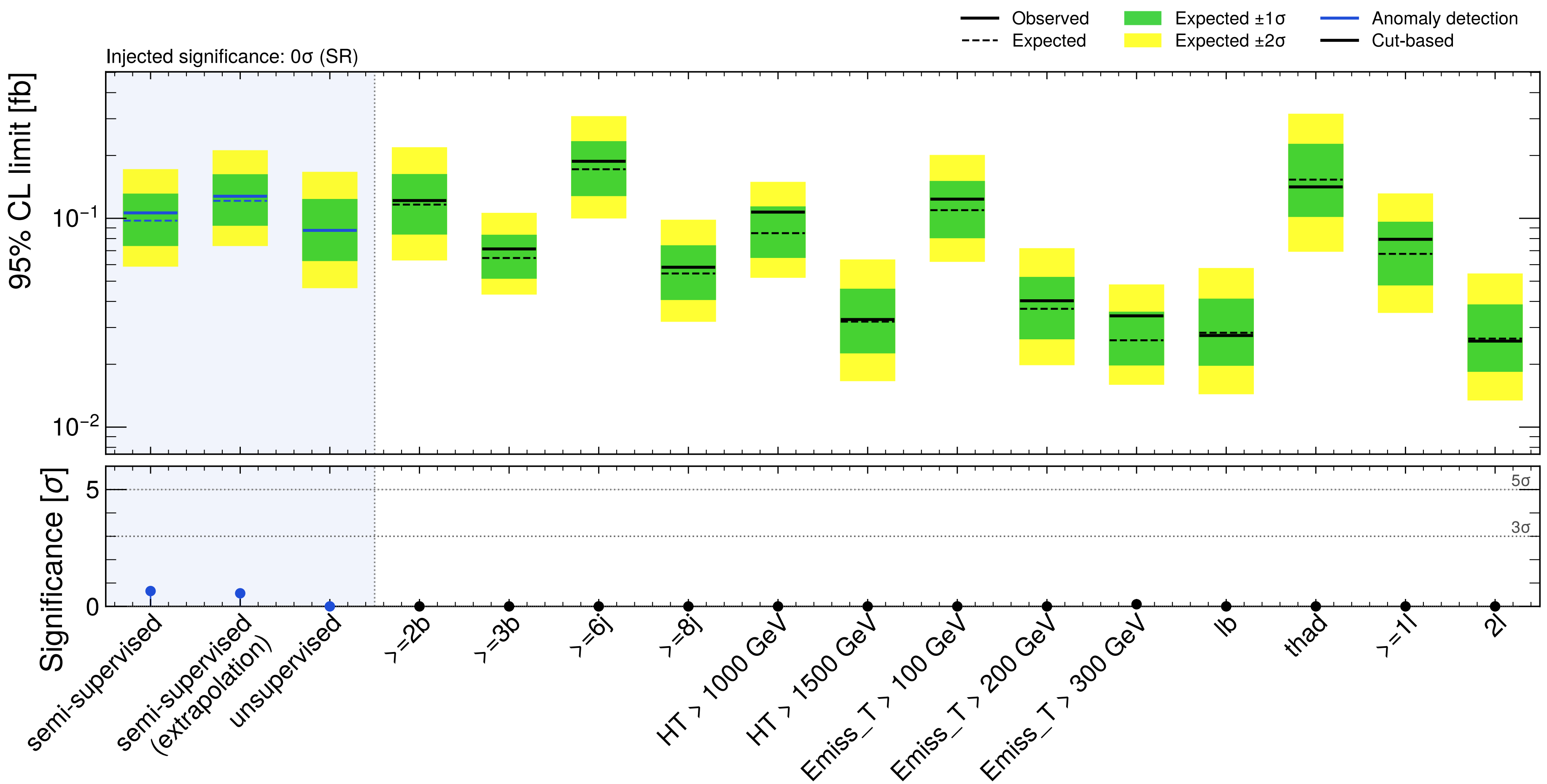
- Cut makes anomaly visible and highly significant
- Use CLs method to extract **model-independent**
- Use signal calibration to extract **model-dependent limits**





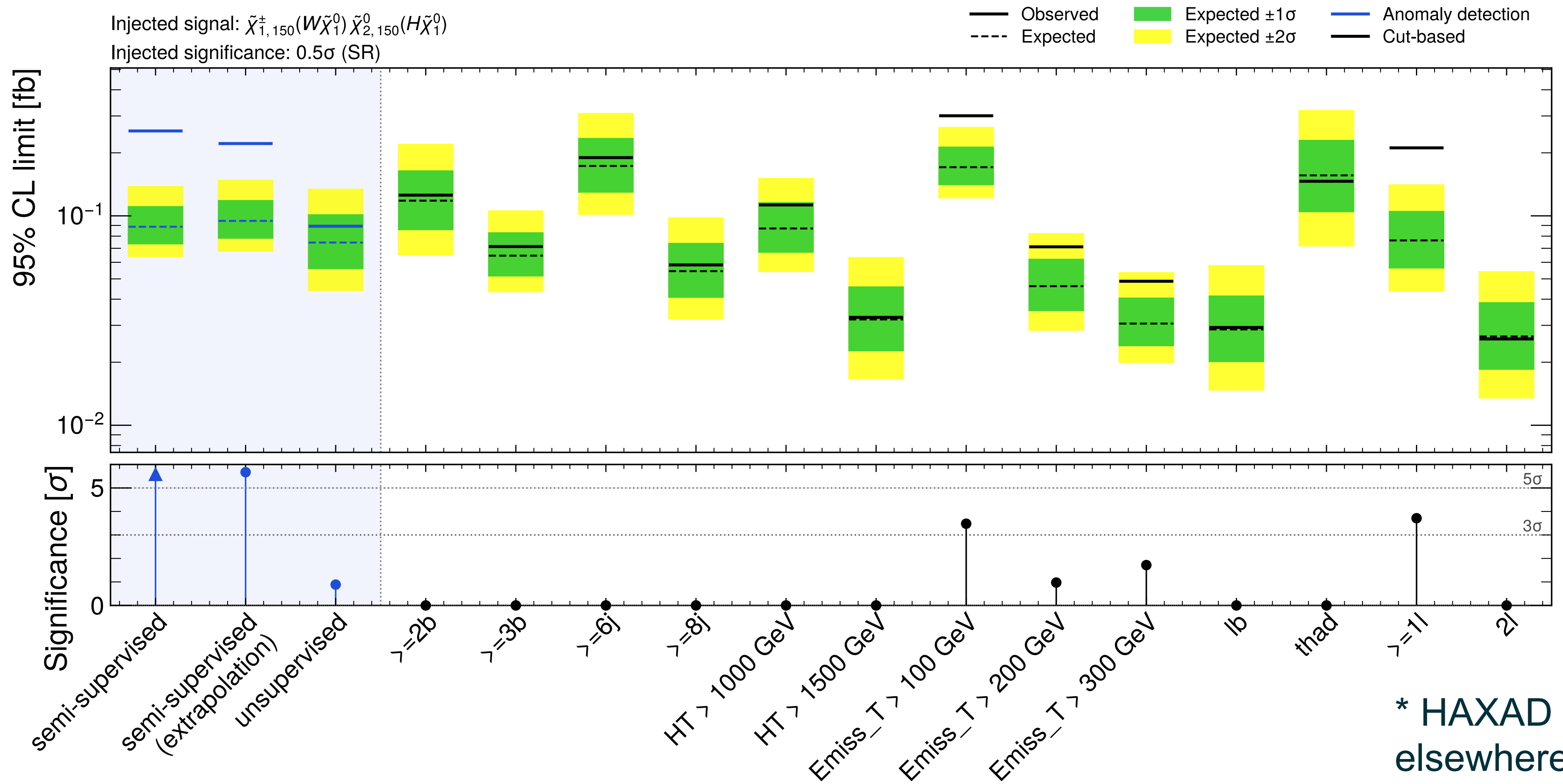
Model-independent Limits

- Model-independent limits are the main result of an anomaly detection analysis
- **Without signal**, the limits are only driven by efficiency (0.5%)



Model-independent Limits

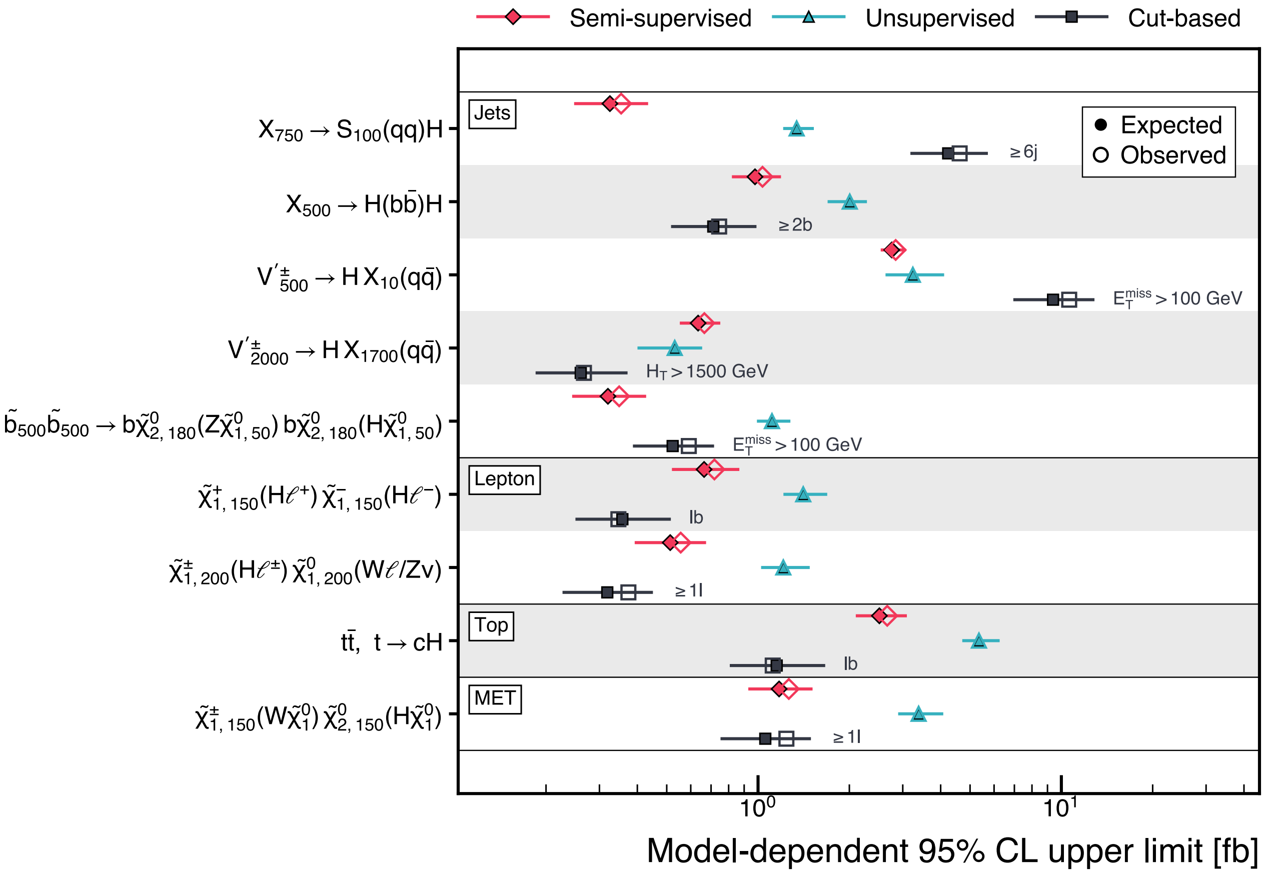
- Model-independent limits are the main result of an anomaly detection analysis
- **Without signal**, the limits are only driven by efficiency (0.5%)
- **With signal** (exemplary process), HAXAD performs better (>5σ) than representative cut-based analysis



* HAXAD has reduced look-elsewhere-effect

Results

- Benchmarking analysis strategy on many signals
- Broad sensitivity and often on-par or better than representative cut-based analysis



*Also HAXAD has reduced look-elsewhere-effect

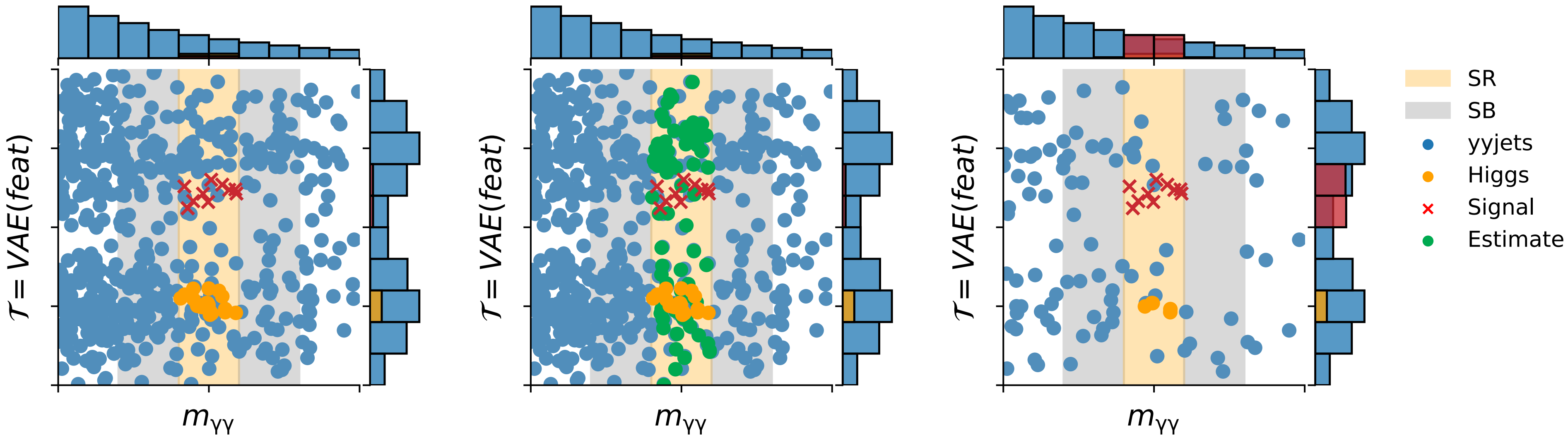
Summary

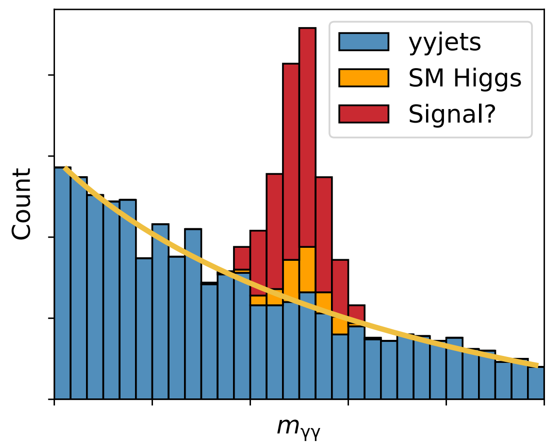
- Anomaly Detection can provide generic and broad sensitivity
- **Now it can also find anomalies in the presence of known signals**
- Technique:
  - Latent space Embedding (2 strategies)
  - Background estimation (ML & Simulation)
  - CWoLa Classification
- What's next: Apply to real data!

Backup

Pipeline

1. **Latent Embedding:**
   - Physics features (feat)
   - **V**ariational **A**uto**E**ncoder
2. **Background est.:**
   - yyjets: Normalizing flow
   - SM Higgs: Simulation
3. **Signal Classification:**
   - CWOLA Approach
   - Bkg. est. vs data
4. **Inference**
   - Exponential fit in SB
   - Measure σ in SR





SupCon Loss

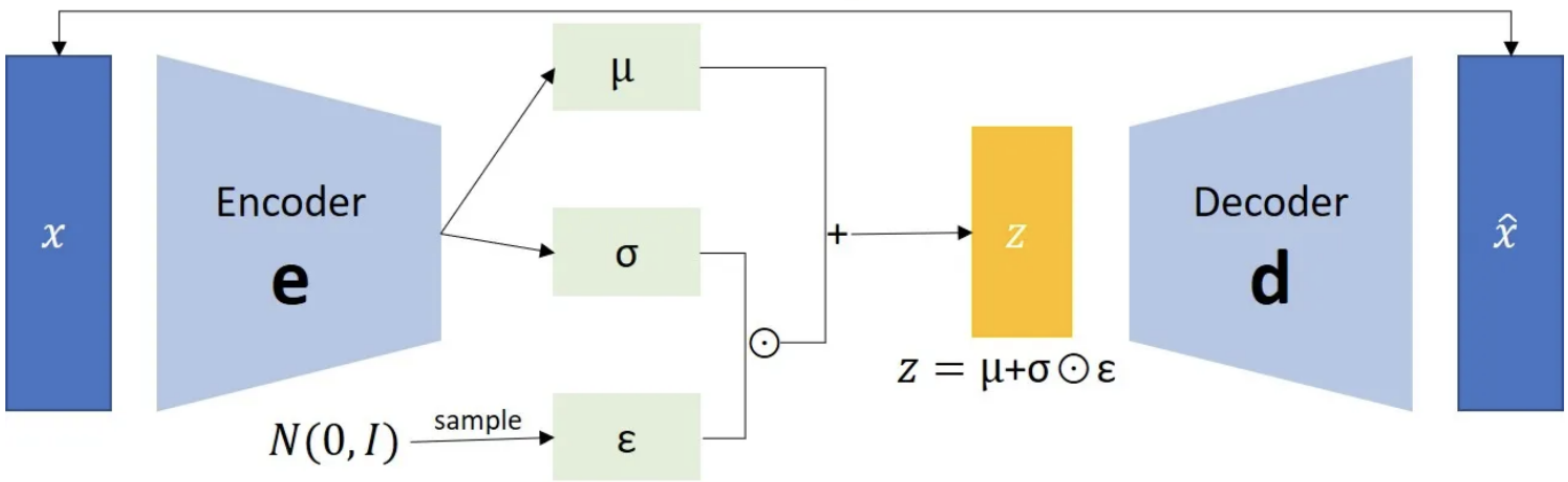
$$\mathcal{L} = \mathcal{L}_{\text{con}} + \lambda \, \text{KL}(z \,\|\, \mathcal{N}(0,1)) \quad \text{with}$$

$$\mathcal{L}_{\text{con}} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(Z_i \cdot Z_p / \tau)}{\sum_{a \in A(i)} \exp(Z_i \cdot Z_a / \tau)}$$

- N indices in a batch I with indices i and physics process labels y_i
- z_i = latent vector from the encoder output
- Z_i = corresponding projection-head output
- All neighbors: $A(i) \equiv I \backslash \{i\}$
- All neighbors with the same physics process label: $P(i) \equiv \{p \in A(i) : y_p = y_i\}$
- Two terms:
  - Contrastive Loss (SupCon)
  - Kullback-Leibler (Gaussian)

Latent Space Embedding (VAE)

- Latent space embedding:
  - Train a Variational Autoencoder (VAE) in SB region (**background only**)
  - Take the encoder part to encode all data into latent space
  - Generate (CATHODE) and classify data directly in the latent space



Why BDTs? (2309.13111)

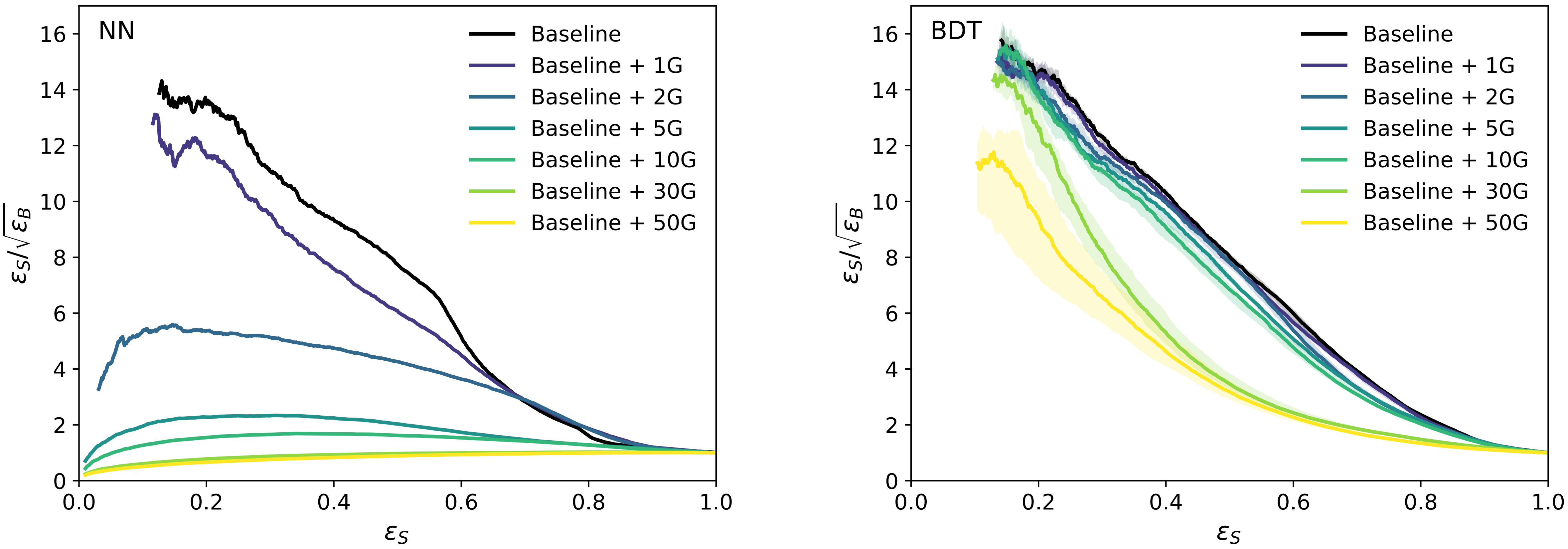
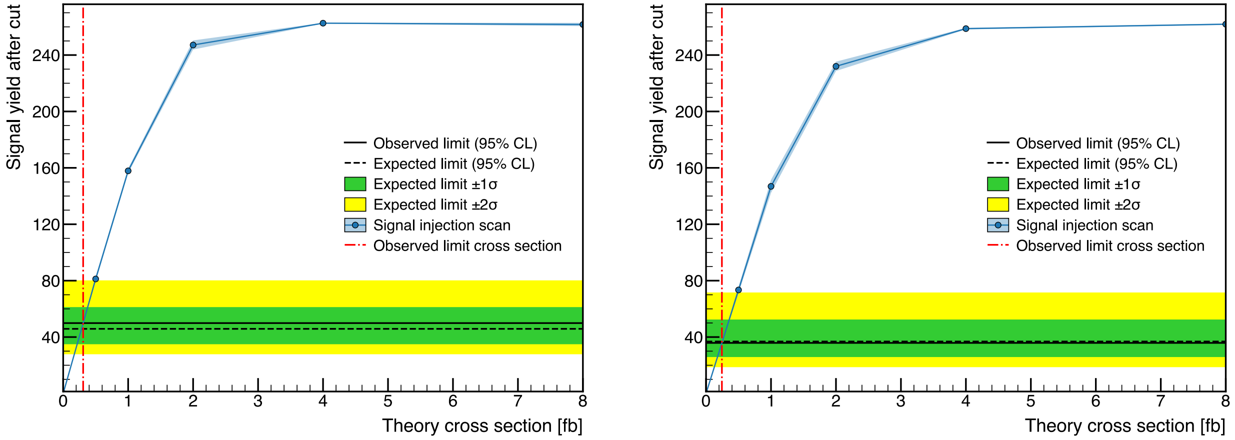


FIG. 2. The impact of uninformative features on the NN and BDT classifiers. We show the SIC curves of the IAD NN/BDT classifiers employing the four baseline features and additional 1, 2, 5, 10, 30 and 50 input features drawn from Gaussian noise (left/right panel). For 30 and 50 Gaussian noise features, BDT classifiers with $N = 100$ are used instead of the usual $N = 50$ ensembling.

Contrastive Embedding Inter- and Extrapolation

Interpolation:

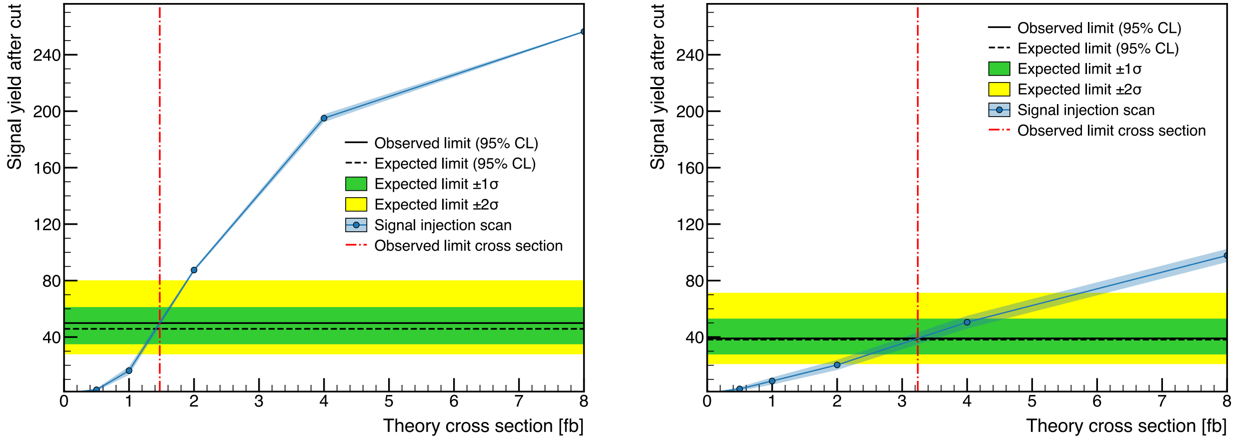


(a) In Dataset

(b) Interpolation

Figure 9. Limit-setting scan for $\tilde{\chi}^{\pm}_{1,400}(H\ell^{\pm})\,\tilde{\chi}^{0}_{1,400}(W\ell/Z\nu)$. The number of injected signal events passing the selection is shown as a function of the injected cross section, together with the model-independent upper limit on the number of signal events N; the vertical dash-dotted line marks the resulting model-dependent cross section limit. Figure 9a shows the results with $\tilde{\chi}^{\pm}_{1,400}(H\ell^{\pm})\,\tilde{\chi}^{0}_{1,400}(W\ell/Z\nu)$ included in the training dataset of the contrastive encoder. Figure 9b shows the results with the $\tilde{\chi}^{\pm}_{1,400}(H\ell^{\pm})\,\tilde{\chi}^{0}_{1,400}(W\ell/Z\nu)$ mass point held out from the training.

Extrapolation:



(a) In Dataset

(b) Extrapolation

Figure 10. Limit-setting scan for $V'^{\pm}_{2000} \to H\,X_{300}(q\bar{q})$, presented as in fig. 9. Figure 10a shows the results with $V'^{\pm}_{2000} \to H\,X_{300}(q\bar{q})$ included in the training dataset of the contrastive encoder. Figure 10b shows the results with all $V'^{\pm} \to H\,X(q\bar{q})$ models held out from the training.